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MODERATING EFFECT OF TITLE IV-E TRAINING ON PUBLIC CHILD WELFARE
TURNOVER

BY

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DISSERTATION

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TURNOVER

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Abstract

Turnover within public child welfare (PCW) has been high for decades, and the problem persists through the present day. Title IV-E training stipends have been employed as one method of increasing retention, but recent legislation could threaten continued allocation of these funds. There is a limited body of evidence suggesting Title IV-E training could be beneficial for retention, and that different factors are salient for turnover intentions among Title IV-E-trained workers. However, these results are far from definitive. The current study fills this research gap by analyzing a causal model of turnover intention, with the ability to compare Title IV-E recipients and non-recipients. Multiple-group path analysis revealed several differences between Title IV-E recipients and non-recipients, and some of these differences are indicative of Title IV-E's possible benefit in reducing turnover. Title IV-E may provide a protective factor against the tendency for MSW graduates and workers in urban locations to express lower intent to remain employed. However, Title IV-E did not buffer against dissatisfaction with other workplace factors, including professional development opportunities, relationships with coworkers and supervisors, workload, and salary. Beyond the substantive findings, many recommendations for future research are provided. This innovative research design provides a template for further inquiry into the contribution of Title IV-E, not only to stem turnover but, ultimately, to improve outcomes for system-involved children and families.

Keywords: public child welfare, turnover, turnover intent, retention, job satisfaction, Title IV-E, multiple-group, multiple-sample, path analysis, causal model, Monte Carlo power analysis

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Moderating Effect of Title IV-E Training on Public Child Welfare Turnover

Chapter 1: Introduction**Problem Statement and Significance**

High turnover among public child welfare (PCW) workers is a decades-old problem that remains to this day. Nationwide, average employment duration of PCW workers is two years, and many supervisors have only three years' experience (Pollack, 2008). This is particularly striking given it takes approximately two years to fully train a PCW worker (Ellett & Leighninger, 2006). Annual voluntary turnover rates within individual agencies can exceed 50%, although 20%-40% appears to be the norm (Curry, McCarragher, & Dellmann-Jenkins, 2005), and it takes an average of seven to 13 weeks to fill vacancies (Westbrook, Ellis, & Ellett, 2006). According to Balfour and Neff (1993, p. 475), "turnover rates above 20 percent should be considered a direct threat to the organization's stock of human capital and its overall effectiveness."

During the five years preceding the year of data collection (2004-2008), annual turnover in the target agency of the present study varied from approximately 21% to 33%, excluding involuntary turnover (i.e., promotions, terminations, transfers, deaths, retirements) (*A better understanding of caseworker turnover within child protective services*, 2009). The situation did not improve by 2012, when turnover rates exceeded 30% in five out of 11 regions and up to 16% of positions unfilled in some regions (Keel, 2013). Over the past ten years, the turnover rate in this agency has averaged about 19% per year, with three years exceeding 20% ("Child protective (CPI/CPS): Staff turnover," n.d.).

Previous researchers have identified four types of costs associated with turnover: separation (costs associated with out-processing), replacement (costs associated with recruitment

and selection), training, and performance differential (costs associated with less experienced, less efficient new hires' performance compared with departed employees who ostensibly had greater job-related competence) (Graef & Hill, 2000). In general, financial turnover costs are estimated between a third and a half of annual worker salary (Zlotnik, Strand, & Anderson, 2009). In the present study's agency, the cost is approximately \$62,500 (2019 dollars) for each worker who leaves; the total cost to the state in 2006 was \$56 million, or about \$71 million in 2019 dollars (Willis, Chavkin, & Leung, 2016a). Beyond financial costs, workloads and associated stress is increased for remaining workers as suitable replacements are recruited and trained, a process which may take up to two years (Ellett & Millar, 2004). This can lead to a cyclical effect, wherein turnover begets more turnover. This effect was found in a 2012 audit of the agency that is the focus of the present study, which revealed high turnover lead to higher workload for remaining workers (inherited cases), which in turn lead to more turnover (Keel, 2013).

High turnover can also negatively influence child welfare outcomes. In a focus group study of system-involved youth, Strolin-Goltzman, Kollar, and Trinkle (2010) reported the relationships children form with their caseworkers can be as strong as relationships with caregivers. However, frequent turnover tends to harm relationships between PCW workers and clients and may delay important decisions as newly assigned workers familiarize themselves with cases (Westbrook et al., 2006). Moreover, Hess, Folaron, and Jefferson (1992) found high worker turnover led to inappropriate reunification of children with their families, and Strolin-Goltzman et al. (2010) found a positive association between number of caseworkers and number of placements (i.e., lack of stability) for system-involved youth. In general, turnover contributes to de-professionalizing the PCW field because it is challenging to maintain an effective workforce under conditions of high turnover.

One way that child welfare jurisdictions have attempted to address staffing shortages is providing training stipends for existing and prospective workers. Since the 1980s the government has spent millions each year on training reimbursements for PCW workers in an effort to reduce high turnover rates. These stipends, funded under Title IV-E of the Social Security Act, are used to offset costs of obtaining professional child welfare training, such as a social work degree. Training stipends are, however, only one small part of federal funding authorized by Title IV-E of the Social Security Act. The overall purpose of Title IV-E is to support children in out-of-home care, and funds are allocated to a variety of purposes, including direct costs associated with care of children, administrative costs, and recruitment and training of foster parents ("Title IV-E: Federal payments for foster care and adoption assistance," 2019). With recent passage of the Family First Prevention Services Act of 2018, states can now also use these funds for prevention services designed to allow children to remain with family members instead of congregate care settings ("Family First Prevention Services Act," 2019). The flexibility that comes with this new mandate could dramatically change allocation of Title IV-E funds; without robust evidence of the effectiveness of the training stipends to reduce turnover, this money could be spent elsewhere (Leung & Cheung, 2018).

Prior research on effectiveness of the training stipends in boosting retention is sparse, and the majority of studies employed weak research designs and have yielded inconsistent results. In a review of empirical literature pertaining to PCW turnover spanning the years 1984-2018, the investigator identified only seven studies that assessed the influence of Title IV-E training stipends, of which only three employed multivariate statistical techniques that can control for confounds. While some of the bivariate and qualitative results indicated Title IV-E workers remained longer than their counterparts (Barbee et al., 2009a; Ellett et al., 2007; Jones &

Okamura, 2000), results were weak, non-significant, or inconclusive in others (Jones, 2003; Madden, Scannapieco, & Painter, 2014; Rosenthal & Waters, 2006). The investigator identified seven literature reviews/meta-analyses pertinent to PCW turnover. Strolin-Goltzman, McCarthy, and Caringi (2006) concluded it is unclear whether Title IV-E graduates remain employed longer than other graduates. In a systematic review, DePanfilis and Zlotnik (2008) found only two multivariate studies that included the influence of Title IV-E on retention, only one of which achieved statistical significance. Rubin and Parrish (2012) concluded prior studies have not been able to disentangle the influence of social work degree and receiving Title IV-E training. Hartinger-Saunders and Lyons (2013) stated there is some evidence to suggest Title IV-E stipend receipt is beneficial for retention, but they only identified two studies to support this claim, one of which (Jones, 2003) reported only bivariate results and the other (Gansle & Ellett, 2002) did not provide a comparison of Title IV-E recipients and non-recipients. Reviews by Mor Barak, Nissly, and Levin (2001), Carpenter, Webb, and Bostock (2013), and Kim and Kao (2014) did not even mention Title IV-E.

In a previous study (Carr, Leung, & Cheung, 2018), the investigator found non-Title IV-E trained Master of Social Work (MSW) respondents expressed lower intent to remain employed at their PCW agency than their non-MSW counterparts. This was not surprising since MSW-holding PCW workers often desire more prestigious, higher paying jobs outside PCW (Ellett & Leighninger, 2006). However, this differential was not found among Title IV-E trained respondents. This finding is important since many – though not all – leaders in child welfare view a professional social work education as the best qualification for PCW work (Jones & Okamura, 2000; Zlotnik, 2006; Zlotnik & Pryce, 2013).

Nevertheless, Carr et al.'s (2018) study was exploratory, and the results are only suggestive. The main limitations were omission of moderators and mediators in the model that was tested, although several have been reported in the PCW turnover literature (e.g., Chen & Scannapieco, 2010; Cohen-Callow, Hopkins, & Kim, 2009; Landsman, 2001). These omissions have both statistical and practical implications. From a statistical perspective, omitting moderators yields an incomplete and potentially biased view of relations among variables in the model (Berry, 1993). Moreover, standard regression approaches make the assumption of no causal relations among predictors (i.e., that there are no mediated paths). If such causal relations do exist and they are not explicitly modeled, this assumption is violated and model results can be seriously biased (Achen, 2005). In the previous study, causal relations among some of the predictors were not modeled, although prior empirical evidence suggests their presence. It is important to recheck Carr et al.'s (2018) results in a more comprehensive framework to ensure the suggestive findings still hold.

From a practical perspective, excluding mediated or indirect effects rendered it impossible to determine the mechanisms or paths of influence underlying turnover intentions and how they might differ for respondents who received Title IV-E training. For example, Carr et al.'s (2018) results indicated Title IV-E training might provide a buffer against the tendency of MSW graduates to want to exit PCW, but it was not possible to determine how this buffering effect might work. It could be that different workplace factors or personal attributes (such as possession of an MSW degree) contribute to job satisfaction, and subsequently reduced turnover intentions, for Title IV-E recipients and non-recipients, respectively. Knowledge of these differences could, in turn, help agency managers target interventions on those aspects of the job

and working environment that matter most to Title IV-E recipients and non-recipients, respectively.

Current Study and Specific Aims

The current study extends Carr et al.'s (2018) contribution in two important ways. First, it includes indirect effects, wherein the influence of an antecedent variable on an outcome is mediated by one or more other variables, revealing the underlying mechanism of influence. Second, interaction effects among selected variables are included, thus accounting for situations wherein the influence of an antecedent on an outcome is dependent upon a third variable (Aiken & West, 1991). As with the original study, the present inquiry will incorporate comparisons of Title IV-E training recipients with non-recipients, but with mediated and moderated effects included. Through the use of this methodology, the investigator will be able to determine if IV-E training moderates the relationship between the MSW degree and turnover intention as well as describe more clearly the mechanism through which this process may occur.

Structural equation modeling (SEM) provides the statistical framework to compare the process underlying turnover intentions for Title IV-E recipients and non-recipients. SEM is a powerful tool that can help reveal complex patterns of association among many variables (Bollen, 1989). It has been used in some of the more robust studies of PCW turnover (e.g., Auerbach, McGowan, Ausberger, Strolin-Goltzman, & Schudrich, 2010; Hwang & Hopkins, 2015; Lee, Forster, & Rehner, 2011a; Lee, Rehner, & Forster, 2010), but it has not been employed to study the influence of Title IV-E training on turnover. In the present study, SEM is used to determine (a) if the direction of influence among variables follows particular paths and (b) whether these patterns are different for recipients of Title IV-E training. This will support the following specific aims:

- Specific aim 1: Test a causal model of turnover intentions. The investigator hypothesizes that individual worker characteristics and perceptions of work environment will indirectly influence turnover intentions via job satisfaction.
- Specific aim 2: Identify differences in the causal model between Title IV-E recipients and non-recipients. The investigator hypothesizes that individual worker characteristics and perceptions will influence job satisfaction and turnover intentions to a lesser degree among Title IV-E recipients.

Identifying whether the process underlying turnover intentions is different for Title IV-E recipients has two implications: (a) document possible benefits of the Title IV-E program in boosting retention and (b) help identify factors most important for retaining Title IV-E workers, twin goals originally articulated by Leung, Brown, Chavkin, Fong, and Urwin (2010). Weaver, Chang, Clark, and Rhee (2007) stated agency managers and administrators can more easily influence some workplace factors than others. If Title IV-E recipients' turnover intentions are less influenced by workplace stressors that are difficult for agency managers to directly control (e.g., compensation, workload), this would provide an indication the training helps boost retention. On the other hand, identifying factors salient to Title IV-E recipients' turnover intentions that agency managers *can* influence (e.g., professional development opportunities, style of supervision) will help managers focus on the aspects of the job that matter most for retaining this highly trained segment of the workforce.

Prior findings from several studies (e.g., Barbee, Rice, Antle, Henry, & Cunningham, 2018; Lizano & Mor Barak, 2015; Rao Hermon, Biehl, & Chahla, 2018) indicate different factors might be relevant for job satisfaction and retention of Title IV-E recipients and non-recipients, respectively. But limitations in the methods these studies used prevented them from

answering the main research question of the present study, namely whether the process underlying turnover intentions is different for Title IV-E recipients. Acknowledging this limitation, Barbee et al. (2018) concluded path analysis is necessary to determine the relations among constructs associated with PCW turnover and how these relations might be different for Title IV-E-trained workers, which is exactly the focus of the present study.

Summary

This chapter provided the basic justification and aims of the present study. Turnover within PCW has been high for decades, and the problem persists through the present day. This problem not only burdens budgets, it also can negatively influence outcomes for system-involved children and families. Title IV-E training stipends have been employed as one method of increasing PCW retention, but recent legislation could threaten continued allocation of these funds. Prior research into the effectiveness of Title IV-E training stipends toward reducing turnover are relatively sparse, and many of these studies featured rather limited research methods. The main goal of the present study is to extend preliminary findings by Carr et al. (2018), who found MSW graduates who are Title IV-E recipients may be less likely than non-stipend MSWs to express lower intent to remain employed when compared with non-MSW graduates. Building upon this prior study using a causal modeling approach can help illuminate differences in the dynamics underlying turnover intentions among Title IV-E recipients and non-recipients, respectively. This approach will help document beneficial effects of the Title IV-E program on retention, as well as identify particular individual and workplace factors that are most salient to workers within each group. Such insights can inform managers and policymakers how to target retention-focused interventions and initiatives.

Chapter 2: Literature Review

In order to understand how the mechanisms underlying turnover intentions might differ among Title IV-E stipend recipients and non-recipients, the investigator conducted a comprehensive review of the empirical literature on PCW worker turnover and related constructs. Although this review does not comprise a formal systematic review, a structured process was followed to ensure completeness. The search began with the following literature reviews and meta-analyses related to PCW turnover: Carpenter et al. (2013); DePanfilis and Zlotnik (2008); Hartinger-Saunders and Lyons (2013); Kim and Kao (2014); Mor Barak et al. (2001); Rubin and Parrish (2012); Strolin-Goltzman et al. (2006). The reference lists for each of these systematic reviews and meta-analyses were reviewed for relevant content, along with the reference lists of each individual study. To check for additional articles that might have not been included in these reviews, the investigator performed searches of the Social Work Abstracts and PsycINFO databases for relevant content. The search was limited to empirical (quantitative or qualitative), peer-reviewed scholarly studies of U.S.-based PCW workers. The only exception was Lambert, Lynne Hogan, and Barton (2001), which included a nationally-representative sample of all U.S. workers, not limited to PCW. This article was included because it provided the foundation for a subsequent study by the lead author (Lambert, Cluse-Tolar, Pasupuleti, Prior, & Allen, 2012), which tested a causal model of turnover intent among social workers. Seventy-seven empirical studies pertaining to outcomes of interest were included in this review, spanning the years 1984-2018.

This chapter proceeds as follows. The first part briefly reviews the historical context of PCW turnover and how Title IV-E training has been conceptualized as a response. In this portion of the review, additional background information on the program is provided as well as a

summary of the few empirical studies that focused on Title IV-E training in the context of PCW turnover. The conceptual framework used for the present study is then introduced, along with definitions of key constructs. The narrative then turns to empirical evidence supporting the conceptual framework, including the role of job satisfaction as a mediator as well as antecedents of turnover, job satisfaction, and related constructs. The chapter concludes with an exposition of methodological limitations of prior studies and a summary of major findings of the literature review.

Title IV-E as Policy Response to PCW Turnover

In the early 1950s, slightly over half PCW workers had at least one year of graduate social work education; 10 years later, this number dropped to about 30% (Ellett & Leighninger, 2006). In the early 1960s, lawmakers responded by allocating federal funds (via Title IV-B of the Social Security Act) to universities for training grants to defray costs for Bachelor of Social Work (BSW) and Master of Social Work (MSW) degrees (Zlotnik et al., 2009). However, additional legislation in the 1970s created strain on the PCW system, resulting in higher turnover. The Child Abuse Prevention and Treatment Act of 1974 required states to implement comprehensive systems to report abuse or neglect of a child/youth under the age of 18. Accordingly, reports of child abuse and neglect tripled from 1976-1986 and then again doubled from 1986-1993. However, since the PCW system was not accordingly strengthened and funded to accommodate the increased caseload, PCW turnover increased significantly (Ellett & Leighninger, 2006).

Lawmakers again responded in the early 1980s. The Title IV-E Child Welfare Training Program was initiated as part of the Adoption Assistance and Child Welfare Act of 1980 (Hartinger-Saunders & Lyons, 2013). The program offers a 75% match of federal money

(Zlotnik & Pryce, 2013) for both degree-seeking and non-degree seeking (continuing education) professional PCW education. The Title IV-E stipend program is administered by the Children's Bureau within the Department of Health and Human Services and is often used to fund joint training partnerships cooperatively administered by child welfare agencies and schools of social work. Willis, Leung, and Chavkin (2016b) offered a succinct yet comprehensive description of the program:

Title-IV-E funded university-agency partnerships provide educational leave for workers to earn social work degrees, expand field placement opportunities, provide stipends for graduate studies, provide students with stipends to cover tuition and books, specialized curriculum to maximize child welfare competencies, specialized workshop, seminar, and training opportunities, teaching personnel and evaluation, and specialized internships in child welfare agencies. (p. 38)

Current and future workers who receive Title IV-E stipends are usually required to work a minimum of one-to-two years in PCW post-graduation (O'Donnell & Kirkner, 2009b). Title IV-E training programs generally focus on developing a core set of competencies deemed requisite for PCW work (Lizano & Mor Barak, 2015), such as coursework on child abuse and neglect and internships with a PCW agency (Barbee et al., 2018).

Since the late 1980s, Title IV-E training has attracted new students to the PCW field and encouraged current PCW workers to obtain further education in the field (usually an MSW degree) (Zlotnik et al., 2009). The proportion of PCW employees with a social work degree has increased from approximately 28% in 1988 to nearly 40% by 2009 (Auerbach et al., 2010), but the program requires significant spending. In FY 2001 spending on training reimbursements was \$276 million (U. S. General Accounting Office, 2003). More recently, as part of the FY 2017

budget the Department of Health and Human Services Administration for Children and Families requested \$1.8 billion in training stipends over the next 10 years (Benton & Iglesias, 2018).

Despite the increased scope of the Title IV-E stipend program over the last decades, two critical problems remain. Firstly, unwanted turnover rates within PCW remain extremely high. Secondly, research on potential beneficial effects of the Title IV-E stipend program has been limited, both in terms of the number of studies and in the methods used. The next section reviews this body of literature.

Title IV-E Training and Turnover: Empirical Evidence

Quantitative studies.

Only seven quantitative studies identified in this review specifically examined the relation of Title IV-E training and turnover or other related outcomes. Jones and Okamura (2000) found Title IV-E recipients were more likely to remain after three years on the job compared with their counterparts. In a follow up study of the same sample (Jones, 2003), there was no significant relation between Title IV-E status and actual retention (now between 2.5 and 5.5 years post-hire) when operationalized as a dichotomous stay/leave indicator, but there was a positive association between Title IV-E status and number of days of employment. Similarly, Barbee et al. (2009a) found a positive association between Title IV-E status and actual retention (two-year follow up). In a follow up study of 73 graduates from a Title IV-E program in Minnesota, only four left the child welfare field after completing their employment obligation, and 52% were still in PCW (Robin & Hollister, 2002), although there was no comparison group in this study. In another follow up study (Barbee et al., 2018), 25% of Title IV-E graduates had left the agency after four years; it took the non-Title IV-E hires only two years to reach this turnover rate. Similarly, Slater, O'Neill, McGuire, and Dickerson (2018) found a higher portion

of Title IV-E BSWs remained through the first five years of employment compared with non-Title IV-E BSWs, although the difference was non-significant in year six. In a preliminary analysis, Rosenthal and Waters (2006) found workers still working under their contractual obligation after receiving Title IV-E stipends were at lower risk for job exit (measured as duration of employment).

Taken together, these findings are suggestive – but not conclusive – of Title IV-E stipends’ beneficial influence on retention, mainly because of methodological limitations. The studies by Jones and Okamura (2000), Jones (2003), Barbee et al. (2009a), and Slater et al. (2018) were bivariate, meaning no confounding factors were controlled. The study by Robin and Hollister (2002) consisted solely of Title IV-E stipend recipients; there was no comparison group. Finally, while Rosenthal and Waters (2006) did employ a multivariate approach, the authors used a payback contract indicator to compare Title IV-E recipients and non-recipients, instead of using an indicator of whether respondents’ had received a stipend. Thus, they compared not Title IV-E recipients and non-recipients, but those who are still under a Title IV-E contractual obligation and all others. The authors did not state why they operationalized the indicator variable in this way, but it is likely because the bivariate effect size was larger for the contract period parameterization. It is of questionable importance merely that those still under contractual obligation remain longer, since it typically takes at least this long to gain full competence as a PCW worker. In addition, the authors included few other covariates (probationary job classification, temporary job classification, job in state office, prior agency employment, and female gender).

Qualitative studies.

Other authors used qualitative methods to compare Title IV-E recipients and non-recipients in terms of retention. Using focus group interviews, Ellett et al. (2007) found participation in a Title IV-E stipend program or an internship emerged as a personal factor contributing to employee retention. Willis et al. (2016b) conducted a qualitative analysis based on several open-ended questions included in the survey questionnaire used by Carr et al. (2018) and the present study. These authors reported on several similarities and differences between Title IV-E stipend recipients and non-recipients, which indicates the process underlying turnover intent could be different for these groups. While relations with colleagues, including coworkers and supervisors, was important for both groups, and workload/caseload was equally important for both groups in terms of leaving the agency, the authors noted several important distinctions between the groups. Non-Title IV-E workers more frequently expressed assisting children and families as a prime reason for remaining employed, although the difference was small (33% versus 29%). Moreover, Title IV-E workers more often expressed overall job satisfaction was a primary reason for remaining with the agency, and that pay was a more salient consideration, owing to their higher level of qualification. Similarly, Title IV-E workers more frequently stated their long-term career goals would not be satisfied by remaining at the agency, ostensibly because they feel somewhat overqualified for their present level of responsibility. The authors concluded it is possible Title IV-E training is creating a “paradoxical professionalization” of the PCW workforce, wherein workers are attaining additional, relevant skills, but this very fact compels them to seek more gainful employment elsewhere.

Barbee et al. (2018) had a different narrative regarding why Title IV-E graduates might leave PCW. They postulated Title IV-E trained workers might have unrealistically high

expectations of the job and themselves, ultimately leading to disappointment. Findings from Rao Hermon et al. (2018) supported this notion; they found lower scores on satisfaction with supervisor, self-efficacy, and perceived influence were associated with leaving the organization for Title IV-E recipients, but this pattern was not replicated among non-Title IV-E respondents. The authors concluded “the strong theoretical grounding that Title IV-Es receive through their education might result in significantly higher expectations for the job” (p. 393).

Title IV-E training versus social work degree.

As Rubin and Parrish (2012) pointed out, the influence of Title IV-E training and possession of a social work degree are often confounded in studies of PCW turnover. Similarly, Clark, Smith, and Uota (2013) called for more research comparing Title IV-E MSW graduates with non-Title IV-E MSW graduates. However, Scannapieco, Hegar, and Connell-Carrick (2012) stated they did not distinguish Title IV-E recipients from others with social work degrees since the majority of social work degree programs in the state that was the focus of their study (and the present one) receive Title IV-E funds and therefore most of the curricula are infused with child welfare content. This is not the same, however, as applying for and being selected for a competitive stipend program, and taking many courses geared toward child welfare, as Title IV-E recipients do.

Further limiting the conclusions of prior research, in all the studies discussed previously, the researchers used descriptive (univariate), bivariate, or qualitative methods, so there was no way to disentangle potential confounding between Title IV-E and social work degree status. Furthermore, of the studies identified in this review, nine consisted entirely of Title IV-E stipend recipients, of which five contained solely Title IV-E MSW graduates, while the remaining four did not assess the influence of an MSW degree at all; such research designs preclude

comparisons with workers who do not have a professional social work education, let alone examining potentially different influences of MSW status and Title IV-E training.

Only one study identified in this literature review Madden et al. (2014) used multivariate methods to simultaneously consider the influence of Title IV-E stipend receipt and social work degree status. Madden and colleagues used multivariate survival analysis on a very large sample ($n \approx 9,000$) of PCW workers in the same state that is the focus of the present study, concluding Title IV-E students were more likely to remain than non-Title IV-E students. However, close inspection of the report indicates the researchers' narrative description of their findings contradicts hazard ratios presented in a regression table. This fact, along with inadequate description of the coding scheme used for binary indicators, makes meaningful interpretation of the study difficult.

In sum, while there have been many previous scholarly inquiries into PCW turnover, relatively few specifically assessed the influence of Title IV-E training, and a vanishingly small number have used multivariate statistical approaches, which help control confounding factors such as the MSW degree. While qualitative results from Willis et al. (2016b) are suggestive of differences between Title IV-E recipients and non-recipients in terms of the dynamics underlying turnover intentions, the literature search revealed no quantitative studies that evaluated the influence of Title IV-E education in a causal framework (i.e., with mediators, such as job satisfaction), which would help elucidate the process underlying unwanted turnover. A more comprehensive and nuanced model of turnover is needed to provide robust evidence of the influence of Title IV-E training (if any) on PCW turnover. The next section provides an introduction to the conceptual framework informing the model of turnover intentions employed in the current study.

Conceptual Framework

In the late fifties researchers began developing a path model of turnover, such that job satisfaction influences turnover intentions, which in turn influence turnover (Russell, 2013). In the late seventies researchers extended this model by conceptualizing distal (e.g., undesirable job attributes) and proximal (e.g., job satisfaction) causes or antecedents of quit intentions, with the proximate causes mediating the distal causes (Hom, Lee, Shaw, & Hausknecht, 2017). There is some evidence of the applicability of this model in the field of PCW. Landsman (2001) demonstrated some individual worker attributes, such as perceptions of workload and promotional opportunities, indirectly influence turnover intentions via job satisfaction. For example, workers who perceive relatively high promotional opportunities tended to express higher job satisfaction and, therefore, greater intent to remain employed in their agency. Similarly, Brimhall, Lizano, and Mor Barak (2014) found PCW workers' perceptions of workplace diversity climate (i.e., perceived fairness of employment practices and promotional opportunities) influenced turnover intentions indirectly via job satisfaction.

The current study extends part of Landsman's (2001) model as shown in Figure 1, incorporating a two-group design: those who received a Title IV-E stipend and those who did not. As with prior work in this area by the investigator (Carr et al., 2018), this will enable testing for moderating effects of Title IV-E, but this time using a causal framework with a mediating variable. In this framework, individual worker variables, including demographic characteristics, education status (MSW vs. no MSW), and attitudes toward specific aspects of work, influence turnover intentions indirectly through job satisfaction. This represents the fundamental process through which turnover intentions are hypothesized to be formed. Because the model includes Title IV-E stipend status as a grouping variable, the presence and strength of relations among the

constructs in the model are free to vary across groups. For instance, the salience of compensation or professional development opportunities could be different for workers who attended a Title IV-E training program and those who did not. The pattern of associations among these variables, along with the differences in these patterns across groups (if any), will reveal whether the process underlying turnover intentions are different for Title IV-E recipients and non-recipients. The next section presents a summary of empirical evidence from the PCW turnover literature that supports the conceptual framework.

Empirical Evidence Supporting Conceptual Framework

This section presents definitions of the constructs in the conceptual framework and summarizes empirical literature describing the associations among these constructs. The basic premise of the conceptual framework is that distal antecedents (individual worker attitudes and characteristics) influence turnover intentions indirectly via job satisfaction. Therefore, the studies selected for this literature review included empirical evidence related to antecedents of turnover (or related constructs), antecedents of job satisfaction, and job satisfaction as a mediator of distal antecedents.

Some of the variables in the conceptual model are self-explanatory and easily measured, such as duration of employment or whether a respondent possesses an MSW degree. Others, however, are psychological constructs that must be indirectly measured through one or more questions posed to the respondent (e.g., job satisfaction, work-related self-efficacy). Moreover, some variables in the framework are unique in that some researchers measure them in an objective way while others focus on subjective aspects. For instance, workload could be measured in terms of actual number of assigned cases or as the worker's perception of workload

severity. This section focuses on measurement of the complex, subjective constructs in the conceptual model.

Prior researchers have measured these constructs in a variety of ways, some using published scales and others drafting their own item wording. Because applied social science is often hampered by inadequate attention to measurement (Borsboom, 2006), sample item wording is included in this review where available and relevant. This will also help establish continuity between constructs as operationalized by other researchers and as in the current study.

Turnover, turnover intent, and related constructs.

Previous researchers have operationalized actual turnover/retention in two ways, including (a) a dichotomous retained/not retained outcome and (b) duration of employment. When information on actual turnover is not available (e.g., instances where respondents are still currently employed), some researchers operationalize turnover intentions by asking respondents about their intent to remain in PCW while others ask about workers' intentions to leave the field. In the present study, turnover intentions were assessed rather than actual turnover as this work will focus on those currently employed in PCW.

While reducing actual turnover is the ultimate goal of PCW retention efforts, there is utility in studying turnover intentions. Owing to their strong predictive power, quit intentions have served as a proxy for actual turnover throughout the history of turnover research (Hom et al., 2017; Steel & Ovalle, 1984). Using meta-analysis, Tett and Meyer (1993) characterized turnover intent as the strongest correlate of intent to turnover, although it is not a perfect proxy; they estimated the population correlation between turnover intention and actual turnover to be approximately .65. Within a PCW context, Aarons, Sommerfeld, Hecht, Silovsky, and Chaffin (2009) found a significant association of turnover intent with actual job exit. Using survival

analysis, these authors demonstrated a one-point difference (increase) on a five-point Likert scale assessing turnover intentions was associated with an approximately 40% higher risk of turnover. In Smith's (2005) study, odds of retention for workers who had searched for another job within the previous year were about half the odds of retention for workers who did not look for other employment. Finally, Dickinson and Painter (2009) found the hazard rate for actual job exit increased by about 40% for each point increase on a six-point scale measuring intent to leave; the authors concluded "when it is not possible to access employment records, proxy measures such as [turnover intent] can be a useful predictor of turnover" (p. 202).

Some researchers have used multi-item scales to measure turnover intentions, such as the Intent to Remain Employed – Child Welfare scale (Ellett, 2000). This scale includes nine items, such as "I intend to remain in child welfare as my long-term professional career," "I am actively seeking other employment," and "I am committed to working in child welfare even though it can be quite stressful at times." Other researchers operationalize the construct using a single item, such as "I plan on leaving this agency within the next 12 months" (Griffiths, Royse, Culver, Piescher, & Zhang, 2017) or a dichotomous response variable (0 or 1) based on whether the respondent had thought about leaving in the previous year (Augsberger, Schudrich, McGowan, & Auerbach, 2012).

Outcomes related to turnover and turnover intentions include organizational commitment, career commitment, job and work withdrawal, and job search behaviors. As Lambert et al. (2012, p. 70) explained, organizational commitment "is the bond between the worker and the organization" and encompasses loyalty, identification with the organization, and involvement in organizational activities. These authors used six items to measure this construct, such as "I find that my values and the employing organization's values are very similar" and "I really care about

the fate of this place.” Career commitment pertains to respondents’ levels of commitment to remain in the field of child welfare as a career. Kim and Hopkins (2017) measured this construct using eight items such as “If I could do it all over again, I would not choose to work in the child welfare profession.” Job withdrawal is closely associated with quit intentions while work withdrawal implies disengagement from one’s work while intending to remain in the organization (Cohen-Callow et al., 2009). Hopkins, Cohen-Callow, Kim, and Hwang (2010) measured job withdrawal with seven items such as “I am looking to move to another work assignment,” or “How often do you think about resigning from your current job?” while work withdrawal was measured by 16 items relating to undesirable behaviors such as tardiness, absenteeism, and neglecting tasks. Job search behaviors include three facets: thinking about finding alternative employment, looking for alternative employment, and taking active steps to secure alternative employment. The thinking-looking-acting model underpins one of the published scales used to assess turnover intentions in PCW, the Intent to Leave Child Welfare Scale (Auerbach, Schudrich, Lawrence, Claiborne, & McGowan, 2014).

Antecedents of turnover/turnover intent and job satisfaction.

Employment duration.

Many researchers have investigated the relation between employment duration and turnover or related constructs. In this review, 30 empirical studies were identified, of which half contained non-significant findings with respect to the relation between employment duration and the following constructs: actual turnover (Jones & Okamura, 2000; Rosenthal & Waters, 2006), further employment duration after a practice-oriented intervention (Aarons et al., 2009), turnover intentions (Boyas, Wind, & Kang, 2011; Boyas, Wind, & Ruiz, 2015; Ellett, 2000; Lee et al., 2011a; Lee et al., 2010; Lee, Weaver, & Hrostowski, 2011b; McCrae, Scannapieco, &

Obermann, 2015; Mor Barak, Levin, Nissly, & Lane, 2006; Nissly, Barak, & Levin, 2005), job search behaviors (Hopkins et al., 2010), and work/job withdrawal (Cohen-Callow et al., 2009; Hopkins et al., 2010).

However, several authors reported longer employment duration was positively associated with retention-related outcomes, including actual turnover (Benton, 2016; Smith, 2005) and turnover intentions (Kim & Mor Barak, 2015; Lambert et al., 2012; Lambert et al., 2001; Landsman, 2001). In a study by (Curry et al., 2005), higher longevity was associated with lower odds of leaving the agency, but only for high experience workers (i.e., four or more years of service). Strolin-Goltzman, Auerbach, McGowan, and McCarthy (2007) and McGowan, Auerbach, and Strolin-Goltzman (2009) found employment duration to be negatively associated with turnover intentions, but only for urban workers, suggesting the presence of an interaction effect. Notwithstanding these indications of the positive influence of experience on retention, two studies contain evidence to the contrary. Hopkins et al. (2010) reported increased work experience actually predicted higher levels of work withdrawal, although they did not speculate why this might be. Similarly, Lambert et al. (2012) reported longer employment duration was associated with lower organizational commitment, although again the authors offered no explanation.

In the agency examined in the present study, actual turnover was lower for workers with longer employment history at the agency (*A better understanding of caseworker turnover within child protective services*, 2009). That is, workers who had been in service longer were less likely to depart than their less experienced colleagues. In an internal audit of the same agency, Keel (2013) noted salaries were competitive for new hires, but far less so for more experienced workers and as a result, promotional opportunities could be especially important for the retention

of veteran employees. It stands to reason that the influence of satisfaction with salary and promotional opportunities, respectively, could have differential influences on job satisfaction, turnover intent, and related phenomena by virtue of workers' employment duration.

To this end, some empirical studies show that time — either in the form of worker age or employment duration — can have a moderating influence on antecedents of job satisfaction, turnover intentions, and related constructs. As Rycraft (1994) stated, employees who have served their agencies longer may feel more invested in the organization, and they generally will have greater earnings, recognition, and standing within the organization. They also tend to develop stronger feelings about commitment to PCW work: "Looking back, it was rocky going in the early years, but we are survivors and it's worth it. I feel I'm doing something of value." (Rycraft, 1994, p. 77).

Given the changes in employees' perspectives as their experience grows, it is quite likely the dynamics underpinning job satisfaction and turnover intentions might be somewhat different for workers of varying employment duration, and several findings indicate employment duration may moderate the association of other variables and retention-related outcomes. For instance, time can influence the potential of supervisor support to buffer against challenging workplace dynamics such as high workload, as discussed in detail below in the section titled Social Integration. It also appears that differences between PCW workers with social work degrees and those without tend to change over time. In a study by Scannapieco et al. (2012), self-efficacy and satisfaction with various aspects of the job (e.g., workload, opportunities for advancement) were higher for social workers than non-social workers at time of hire, but the situation had reversed after 18 months on the job. These differences disappeared after three years on the job, although there were still differences between the groups in terms of career aspirations and turnover intent:

social workers had higher commitment to the overall profession of social work, but expressed lower commitment to PCW in particular. Retention at the three-year mark was also statistically significantly higher for holders of social work degrees (51% versus 43%).

In terms of job satisfaction, five of eight studies (Barth, Lloyd, Christ, Chapman, & Dickinson, 2008; Lambert et al., 2012; Landsman, 2001; Lizano & Mor Barak, 2015; Mor Barak et al., 2006) found no significant association between employment duration and job satisfaction. Furthermore, all these studies incorporated multivariate approaches, and one (Lizano & Mor Barak, 2015) even compared Title IV-E recipients and non-recipients, as discussed previously. Nevertheless, three other authors did find a significant association, also using multivariate techniques. Lambert et al. (2001) and Strand and Dore (2009) both reported a negative association between employment duration and job satisfaction. Recall the Lambert et al. study consisted of a nationally-representative sample of workers, not limited to a specific sector. The authors concluded their finding was not necessarily surprising since the prior empirical literature was mixed, and since “in some organizations, senior workers are highly respected and rewarded, while in others, high tenure is viewed as a liability” (Lambert et al., 2001, p. 245). Strand and Dore (2009) did not offer an interpretation of their findings.

Schweitzer, Chianello, and Kothari (2013) did not study the influence of employment duration per se on job satisfaction, but they did assess number of years practicing with an MSW degree. This measure should be at least roughly analogous to employment duration since nearly all their sample (92%) held MSW degrees. Contrary to Lambert et al. (2001) and Strand and Dore (2009), Schweitzer et al. (2013) indicated a positive association between number of years and job satisfaction. The authors hypothesized this might be since higher compensation tends to come with increased work experience. However, this explanation seems implausible since salary,

form of compensation, and contentment with income were controlled. However, these were the only other variables in the regression model, so it is possible years practicing as an MSW graduate is a proxy for some other important variable that influences job satisfaction, such as perhaps commitment to child welfare work or work-related self-efficacy, as discussed previously. Nevertheless, the authors rightly concluded “In order to more fully understand this relationship, it may need to be the focus for further research” (Schweitzer et al., 2013, p. 154).

In summary, for both turnover-related constructs and job satisfaction, results of prior empirical work examining employment duration are varied. In addition to a mixture of significant and non-significant findings, significant results were obtained in both directions, with longer employment duration sometimes being associated with retention and higher job satisfaction, and other times being associated with turnover and lower job satisfaction. What is clear is that employment duration is an important influence on turnover and job satisfaction, perhaps as a moderating factor for other influences, such as possession of a social work degree.

Professional training (social work degree).

The discussion in this section presents an overview of empirical findings pertaining to the relation of a professional social work education (i.e., BSW or MSW) and PCW turnover, with an emphasis on competing narratives and limited research methods employed. Training that is not related to obtaining a social work degree is discussed in the next section.

In contrast with the limited literature on Title IV-E, there is a greater number of prior studies that have examined the relation between turnover (and other related constructs) and holding a social work degree, and findings are mixed. Of the 20 such studies identified in this review, in four of them researchers found no significant association between actual turnover and possession of an MSW degree (Jones, 2003; Jones & Okamura, 2000; Rosenthal & Waters,

2006; Weaver et al., 2007), and in another four there was no significant relation with turnover intent (Landsman, 2001; Lee et al., 2010; Lee et al., 2011b; McCrae et al., 2015). Finally, Hopkins et al. (2010) found no relation between MSW status and job or work withdrawal, and Kim and Hopkins (2017) found no significant association between MSW status and organizational commitment.

Conversely, several authors reported statistically significant relations between social work degree status and actual or intended turnover. Dickinson and Painter (2009), Hopkins et al. (2010), Jones (2003), and Yankeelov, Barbee, Sullivan, and Antle (2009) all reported MSW graduates had higher actual turnover, while Auerbach et al. (2010), Dickinson and Painter (2009), Kruzich, Mienko, and Courtney (2014), and Weaver et al. (2007) found higher intended turnover among MSW graduates. Similarly, Augsberger et al. (2012) found a positive association between holding a social work degree (not limited to MSW) and turnover intent. On the other hand, results from Shim (2010) indicated turnover intentions were lower among MSW respondents, and Smith (2005) found social work degree holders were less likely to turnover within a 15-17 month follow-up period, although the entire sample consisted of rural PCW workers, and therefore the findings may not generalize to urban workers. For example, Strolin-Goltzman et al. (2007) found social work degree holders (BSW or MSW) expressed higher turnover intentions, but only among urban workers.

Other authors reported mixed findings as well. Chenot, Benton, and Kim (2009) found MSW graduates expressed higher turnover intentions, but only among early career workers. These results suggest interaction effects, wherein the influence of social work degree on turnover intent depends upon other factors such as employment duration and location. Finally, in a follow-up study Jones (2003) found no significant relation between MSW status and actual turnover

when operationalized as a dichotomous retained/not retained indicator, but MSW graduates had a longer employment duration.

In terms of job satisfaction, four of the identified studies contained findings related to social work degree status. Landsman (2001) did not find a significant relation between job satisfaction and social work degree status (BSW or MSW), but Barth et al. (2008) and Glisson, Green, and Williams (2012) found holders of social work degrees expressed higher job satisfaction; these latter two studies are particularly important since they included a nationally-representative sample of PCW workers. Kim and Hopkins (2017) found just the opposite, however, at least among urban respondents (the effect was non-significant for rural respondents). While neither Kim and Hopkins (2017) or Glisson et al. (2012) offered any substantive explanations of their findings, Barth et al. (2008, p. 207) stated “social workers might be more willing to endure a mediocre sense of satisfaction because of a commitment to social work values and a clearer understanding of the dynamics of child maltreatment and the policies intended to address them.” However, Rubin and Parrish (2012) offered a somewhat different perspective, that holders of social work degrees may have higher expectations going into the profession than non-social workers, and thus experience lower job satisfaction. Regardless, the relation between social work degree status and job satisfaction is not clear.

Professional development.

Professional development generally refers to opportunities for growth and enhancement (including but not limited to promotional opportunities) an employee perceives are available within their agency. Professional development can also refer to optional training opportunities not related to receipt of a Title IV-E stipend or obtaining a social work degree, such as on-the-job training and continuing education. For example, Dickinson and Perry (2003) measured

professional development with items asking about “opportunities for personal growth and development,” “opportunities for promotion,” and “opportunities for improving knowledge and skills.”

Several studies revealed professional development opportunities may aid in PCW retention. In semi-structured interviews comparing stayers vs. leavers, Samantrai (1992) found lack of promotion/transfer opportunities catalyzed intention to quit. An audit of the present study’s focal agency revealed increased promotion opportunities could help retain more experienced workers (Keel, 2013). These results were supported by those found in the same agency by Leung et al. (2017). Similarly, qualitative findings from Ellett et al. (2007) and Leung et al. (2010) point to lack of advancement opportunities as an important driver of turnover among PCW caseworkers. Clark et al. (2013) found access to continuing training and support for licensure were positively associated with employment duration. Collins-Camargo, Ellett, and Lester (2012) indicated a positive association with intent to remain employed in PCW. Similarly, Griffiths et al. (2017) found a negative association between professional development and intent to leave the profession, while Kim and Hopkins (2017) found growth and advancement positively predicted organizational commitment and Landsman (2001) demonstrated perceived promotional opportunities predicted intent to remain in PCW.

As with professional training, however, overall findings relating professional development and turnover are mixed. Of 16 empirical studies that included professional development or a similar construct, 11 had non-significant results. Of these, three defined professional development strictly in terms of promotional opportunity, including Jayaratne and Chess (1984), Lambert et al. (2012), and Smith (2005). Dickinson and Perry (2003) defined the concept in terms of promotional opportunity as well as (a) opportunities for growth and

development and (b) opportunities for improving knowledge and skills; they tested these items individually and none were significantly related to turnover. Cahalane and Sites (2008) found no significant association with actual turnover. Neither did (a) Dickinson and Painter (2009), who measured growth and advancement opportunities, (b) Smith and Clark (2011), who asked generically about “growth and development,” (c) Benton (2016), who measured growth and development, or (d) Deglau, Akincigil, Ray, and Bauwens (2018), who measured growth. Moreover, results from Dickinson and Painter (2009) are counterintuitive, as greater perceived growth and advancement opportunities were actually predictive of higher turnover intentions. The authors offered no substantive explanation of the findings beyond a platitudinous “These findings suggest a complex dynamic where multiple and sometimes competing forces are at play” (Dickinson & Painter, 2009, p. 203).

Five studies assessed the influence of professional development on job satisfaction, and all five contained statistically significant results indicating higher perceptions of professional development opportunities correspond to increased job satisfaction. However, one of these studies (Glisson et al., 2012) was excluded since job satisfaction was mixed with other constructs. Jayaratne and Chess (1984), Landsman (2001), Strand and Dore (2009), Potter, Comstock, Brittain, and Hanna (2009) all used multivariate methods to assess the influence of promotional opportunities on job satisfaction, finding a significant, positive relation. Kim and Hopkins (2017) also used a multivariate approach to assess the relation of job satisfaction and growth and advancement, finding growth and advancement significantly predicted job satisfaction among both rural and urban PCW workers. Although the results concerning professional development and job satisfaction are consistent, none of these studies controlled for

receipt of Title IV-E stipends. Therefore, it is unknown if the relation between professional development and job satisfaction is different for these two populations of PCW workers.

Social integration.

Landsman (2001, p. 392) defined social integration as “interpersonal relationships in the workplace,” including relations with colleagues as well as supervisors. There has been much prior empirical work investigating the relation between social integration and turnover and other related constructs. In this review, the investigator identified 48 such articles, including 43 that used multivariate methods, of which 14 used some type of causal modeling, such as path analysis or structural equation modeling. Some studies included measures of both supervisor and coworker relations, while others focused on only one of these.

As is common practice in this field, social integration was measured in a wide variety of ways, including items such as “My supervisor provides the expert help I need to do my job,” “My supervisor encourages coworkers in my unit to help each other with work related problems,” and “My supervisor cares about me as a person” (Dickinson & Painter, 2009). Other researchers focused on the extent to which supervisors encouraged workers to participate in decision making (e.g., Kruzich et al., 2014) or frequency of supervisory input (e.g., McCrae et al., 2015). In terms of relations with colleagues, Jacquet, Clark, Morazes, and Withers (2008) inquired about workers’ perceived support and recognition from peers, while Kruzich et al. (2014, p. 21) studied team psychological safety, which they defined as the degree to which a team is “characterized by interpersonal trust, respect for the competence of all team members, and care and concern about members as people.”

Barbee et al. (2018) and Jacquet et al. (2008) suggested supervisor support could help dampen the ill effects of stress and high caseloads. In semi-structured interviews, Samantrai

(1992) found high quality supervision buffered ill effects on job satisfaction of high caseloads and other potentially problematic conditions: “As long as the supervisor was experienced as supportive and as treating the participants as professionals, all other conditions could be tolerated by the workers. When the supervisor was experienced as critical, nonsupportive [sic], or uncaring, other conditions became intolerable” (p. 456). Mirroring these findings, Rycraft’s (1994) seminal work revealed committed survivors in the PCW field often cited quality of supervision as a decisive factor in retention: “A good supervisor can make a big difference. A not-so-good supervisor can break you” (p. 78).

Similarly, a qualitative study of committed survivors revealed “the relationship dimension in child welfare organizations, making certain workers feel valued by colleagues, supervisors, and administrators, is clearly vital to sustaining employees in difficult times, developing their commitment to child welfare, and enhancing their longevity as employees” (Westbrook et al., 2006, p. 56). Conversely, poor relationships with supervisors can hasten turnover. For instance, in a sample of Title IV-E graduates working in the agency that happens to be the focus of the current study, poor supervision was cited as a reason for leaving (Scannapieco & Connell-Corrick, 2003). In a State Auditor’s Office report on the same population, Keel (2013) revealed similar findings in that exiting workers often cited problems with their supervisor.

Relations with coworkers is a distinct aspect of social integration, and the role of coworker support appears to function somewhat differently from supervisor support. For example, in a study of PCW workers in Georgia, respondents indicated even though they did not feel respected or recognized by their supervisors, and that supervisors did not exhibit leadership characteristics, they did feel supported by coworkers (Williams, Nichols, Kirk, & Wilson, 2011).

Conversely, in a study by Yankeelov et al. (2009) coworker support was not predictive of actual turnover, but closeness of supervisory relations was, with better relations being associated with retention. Similarly, findings from Benton (2016) (who studied actual turnover) and Griffiths et al. (2017) (who studied turnover intentions) indicated supervisor relations were important for boosting retention but coworker relations were not.

However, higher levels of social integration do not necessarily always boost retention-related outcomes, however. Studies by Hopkins et al. (2010) and Boyas et al. (2011) revealed higher levels of coworker support were actually related to increased turnover intentions. Boyas et al. (2011) noted coworkers can provide support for both staying and leaving intentions, depending on the situation and the prevailing norms and attitudes within the organization. For instance, under the stressful conditions that typically prevail in PCW, solidarity among workers can actually serve to encourage thoughts of leaving the organization. As Hopkins et al. (2010, p. 1385) stated, “Perhaps having coworkers who were experiencing similar distress at work translated into norms of engaging in unfavorable behaviors, such as not showing up, failing to attend meetings, and neglecting necessary tasks.”

Further adding to the complexity of this phenomenon, the influence of both supervisor support and coworker support appears to depend on employees’ experience levels, as employees’ needs likely change over the course of their careers. For instance, Cohen-Callow et al. (2009) found stress positively predicted work withdrawal for workers of all ages, but the effect was a bit stronger for younger employees, who ostensibly had less efficacy to deal with the stressors of PCW work. Likewise, Boyas et al. (2011) found job stress was positively related to turnover intent, but only for younger workers.

Curry et al. (2005) found supervisor support was positively related to retention for low experience workers (four or fewer years of experience), but not high experience workers. Moreover, coworker support was also positively related to retention for the low experience group, but negatively related for high experience workers. Chenot et al. (2009) found peer support was important for increasing remain intentions only among early career workers, with higher support corresponding to lower turnover intent; and while supervisor support was positively related to remain intentions, the relation was stronger for less experienced workers. Similarly, Boyas et al. (2011) found a significant association between coworker support and turnover intent only among young workers. However, in this case higher levels of coworker support were associated with higher turnover intent. In a follow up study, these authors found supervisory support negatively associated with turnover intentions for newer workers, but positively predicted turnover intent for more experienced workers (Boyas, Wind, & Ruiz, 2013). In a sample of exclusively experienced, professional (including social work degreed) workers and administrators, Claiborne, Auerbach, Zeitlin, and Lawrence (2015) found supervisor support did not predict job search behaviors. These results were echoed in a qualitative study by Johnco, Salloum, Olson, and Edwards (2014), where supervisors and more experienced case managers reported supervision was not a factor in their decision to remain employed.

Several authors have offered substantive interpretations of why the relation between social integration and turnover could change over time. Curry et al. (2005, p. 942) stated “experienced workers are probably more autonomous and less dependent upon both their supervisors and coworkers for support.” Relatedly, Zinn (2015, p. 109) concluded “more experienced caseworkers may derive less benefit from, or may be more discerning critics of, supervisory support than less experienced workers.” Boyas et al. (2013) speculated using the

same supervisory practices and styles with more experienced workers as are used with newer workers could be off-putting to experienced staff. Dickinson and Painter (2009) noted skilled supervisors can boost retention by tailoring feedback to specific job functions and limiting expectations for newer workers while supplying seasoned veterans with coaching for broader skill development and higher levels of achievement.

In addition to employment duration and age, receipt of Title IV-E training was also reported to moderate the influence of supervisory relations. In a study by Rao Hermon et al. (2018) Title IV-E leavers had significantly lower satisfaction with supervisors vis-à-vis Title IV-E stayers, whereas there was not significant difference between non-Title IV-E stayers and leavers. The authors speculated “that Title IV-Es have specific needs and are more sensitive to the effects of poor culture and climate than non-IV-Es,” (p. 393) indicating this population of workers must be managed differently. Conversely, Barbee et al. (2018) found supervisory support was more salient for turnover intent among non-Title IV-E graduates. One possible explanation is that, unlike in the Rao Hermon et al. (2018) study, Title IV-E graduates had higher work-related self-efficacy, meaning they were less reliant on supervisory assistance. For instance, using qualitative methods, Barbee et al. (2009a) found Title IV-E BSW graduates had higher self-efficacy than non-Title IV-E participants. However, the non-Title IV-E graduates in the Barbee et al. (2018) study actually reported higher self-efficacy, and self-efficacy was a significant predictor of turnover intent only among non-graduates. Although it is difficult to ascertain the direction of the effect because of a lack of multivariate statistical controls, the foregoing studies indicate the relation of supervisor support and turnover intent is likely different for Title IV-E stipend recipients versus non-recipients.

In terms of the relation between social integration and job satisfaction, significant results were reported in eight of 9 empirical studies, although as in the previous section, Glisson et al. (2012) was excluded since a measure of coworker cooperation was mixed with other constructs. Using structural equation modeling on a nationally-representative sample of U.S. workers, Lambert et al. (2001) reported better relations with coworkers predicted higher job satisfaction. Strand and Dore (2009) also found a significant, positive relation between job satisfaction and a composite variable measuring satisfaction with supervision (e.g., help and support from supervisor, regular meetings). Lambert et al. (2012) found similar results using a 10-item scale to measure quality of supervision. Brimhall et al. (2014) measured a comprehensive construct of social integration they termed climate for inclusion, which reflects workers' perceptions they participate in decision making in five realms: work group, organization, supervisor, upper management, and social/informal. They found climate for inclusion is a significant predictor of job satisfaction. Similarly, in a study by Kim and Hopkins (2017) peer cooperation was found to be positively related with job satisfaction. Finally, in a multi-level latent class analysis of public and private CW caseworkers, Zinn (2015) found job satisfaction was 1.28 standard deviation units higher for workers who characterized the relationship with their supervisor as supportive vis-à-vis those with not supportive and critical relationships.

On the other hand, measures of administrative support, supervisor competence, supervisor support, and professional sharing and support were not significantly related to job satisfaction in a report by Potter et al. (2009). Although the authors offered no explanation why this might be, their multiple regression model accounted for some 13 other constructs, and it could be that measures of social integration were not as salient as other factors. Other authors got mixed results. Landsman (2001) found supervisor support was related to job satisfaction, but

coworker support and agency support were not. Using a nationally-representative sample of PCW workers, Barth et al. (2008) found perceived supervision quality (in terms of emotional support and advice) was important for job satisfaction, but the amount of time supervisors spent with their subordinates was not.

In one study, the authors specified a model using social integration as a moderator by dividing the sample into two groups based on a median split of supervisor support. Using multi-group path analysis, Lizano and Mor Barak (2015) found perceived supervisor support did not moderate relations among job demands, job burnout, and job satisfaction; no other studies identified in this review assessed the moderating influence of social integration vis-à-vis job satisfaction. Finally, Barbee et al. (2009a) obtained rather counterintuitive results in a sample of BSW graduates. These researchers measured several domains of social integration with respect to both coworkers and supervisors, including receiving advice/information, tangible support, recognition of competence and skills, and emotional closeness (attachment). In bivariate analyses, all were non-significantly related to job satisfaction except attachment with coworkers: “The more graduates were attached to coworkers, the less satisfied they were with the job” (p. 438). Although the authors offered no explanation for the finding, it parallels results from Hopkins et al. (2010) and Boyas et al. (2011), discussed earlier in this chapter, who found higher levels of social integration were associated with increased turnover intent. It is possible similar dynamics were in play in the Barbee et al. (2009a), such that close relations with coworkers can reinforce negative views about the job. On the other hand, the study only used bivariate methods, and is therefore only suggestive.

Role overload.

As with other constructs discussed in this chapter, researchers have defined role overload in a variety of ways. Landsman (2001, p. 410) used the term work overload, described as the “extent to which performance expectations of the job seem excessive” (e.g., “I do not have enough time to get everything done on the job”). Kim and Hopkins (2017) used the term role overload, measured by items such as “the amount of work I have to do keeps me from doing a good job.” These types of items focus on workers’ perceptions of workload, but some researchers have differentiated perceived workload versus objective measures, such as actual caseload (e.g., Jacquet et al., 2008). Still others (e.g., Dickinson & Perry, 2003; McGowan et al., 2009) have focused on the types of tasks that drive workload, especially tasks that are incidental to working with children and families, such as paperwork and other administrative tasks.

Role overload is an important factor in PCW turnover. Interviews with experienced PCW workers indicated high workloads sometimes translate into after-hours duty that is not compensated, which can lead to burnout and turnover over time (Reagh, 1994). In an audit of this study’s target agency, nearly 30% of workers cited working conditions, including workload, as the reason for their voluntary departure (Keel, 2013). In a qualitative study of both Title IV-E and non-Title IV-E workers, Leung et al. (2010) concluded high caseloads are a contributing factor to turnover.

Of 29 empirical studies identified in this review, 12 contained non-significant findings in terms of the relation of workload and turnover or related constructs, including actual turnover (Benton, 2016; Cahalane & Sites, 2008; DePanfilis & Zlotnik, 2008; Dickinson & Painter, 2009; Smith & Clark, 2011), organizational commitment (Kim & Hopkins, 2017), employment duration (Madden et al., 2014), turnover intentions (Deglau et al., 2018; Dickinson & Painter,

2009; Jayaratne & Chess, 1984; McCrae et al., 2015; Shim, 2010; Weaver et al., 2007), and job search behaviors (Claiborne et al., 2015). In contrast to these null findings, 16 other studies contained significant results supporting lower workload relating to outcomes felicitous for retention for the following criterion variables: actual turnover (Barbee et al., 2009b; Dickinson & Perry, 2003; Hopkins et al., 2010; Smith, 2005; Weaver et al., 2007), turnover intentions (Boyas et al., 2013, 2015; Collins-Camargo et al., 2012; Ellett et al., 2007; Griffiths et al., 2017; Kim & Mor Barak, 2015; McGowan et al., 2009; Mor Barak et al., 2006), job search behaviors (Claiborne et al., 2015; Hopkins et al., 2010), and work/job withdrawal (Cohen-Callow et al., 2009; Hopkins et al., 2010).

Several authors reported mixed or counterintuitive results. For instance, (Landsman, 2001) found work overload was significantly and negatively related to intent to remain in the field of PCW, but was non-significant for intent to remain employed by a particular organization. In a study by Fernandes (2016), lower levels of work overload predicted lower thinking about leaving and lower looking for other jobs, but was non-significant for actively trying to get other employment (e.g., interviews, resumes). Similar to findings related to social integration discussed previously, Boyas et al. (2011) found role overload was positively related to turnover intent, but only among younger workers.

Jacquet et al. (2008) reported counterintuitive findings in their study of Title IV-E recipients. Although *satisfaction* with caseload was significantly related to turnover intentions in the expected direction, *actual* caseload was non-significant, and *perceptions* of caseload was significantly related to actual retention, but not in expected direction. That is, respondents who stayed beyond their contractual work obligation tended to perceive higher caseloads than those who left the agency. The authors suggested commitment to clients may be more important than

high caseloads for those workers who remain in PCW. However, those who remained did indicate they desired lower caseloads so they could perform more traditional social work roles instead of administrative tasks. Curry et al. (2005) also obtained counterintuitive results, in that higher caseloads were associated with retention. The authors speculated supervisors might assign larger caseloads to exemplary workers who can effectively manage the workload, and that new hires might not have yet been assigned a full caseload.

A total of eight studies assessing the relation of workload and job satisfaction were identified in this review, including four with significant findings, one with mixed findings, and the remainder non-significant. Two of the studies with non-significant findings (Glisson et al., 2012; Kim & Hopkins, 2017) and one additional with significant results (Mor Barak et al., 2006) were excluded because role overload was mixed with other constructs. In terms of the significant findings, Landsman (2001) found work overload was inversely related to job satisfaction; Similarly, Strand and Dore (2009) indicated there was an inverse relation between job satisfaction and what they termed working conditions (e.g., inflexible schedule, excessive overtime), and Lambert et al. (2012) found a negative association between job satisfaction and role overload (e.g., unmanageable volume of work, unreasonable job demands). Finally, Potter et al. (2009) reported mixed findings in that time stress negatively predicted job satisfaction in only one wave of two in the study.

In sum, despite some null results, it appears Mor Barak et al. (2006, p. 564) were correct in asserting “Most workers come to the field wanting to help families and children and when their job conditions do not allow them to do a good job, their job satisfaction suffers.” One respondent’s comment during a qualitative study by Jacquet et al. (2008, p. 48) illustrates the importance of this aspect of PCW work: “I have a high caseload and it does not allow me to do

real social work, I spend most of my time doing paperwork, instead building a relationship with my clients.” Thus, prior empirical research generally points to a negative association between workload and intent to remain in PCW and related constructs. However, none of the listed studies included Title IV-E stipend status, so it is unknown what influence this might have on the relation between workload and job satisfaction. The mixed findings by Jacquet et al. (2008) and Curry et al. (2005) indicate more committed and more capable workers could perhaps persevere despite high workloads. Accordingly, a finding that Title IV-E workers’ turnover intentions and job satisfaction were less influenced by role overload would be a positive outcome for the program.

Work-related self-efficacy.

Several researchers have investigated the degree to which confidence in oneself to perform work-related tasks competently fosters intentions to remain in the PCW field. Some investigators have measured self-efficacy with a single item, such as Dickinson and Painter (2009) (“I am confident in my ability to perform this job”) or Benton (2016) (“In your work as a child welfare employee, how would you describe the success you have in accomplishing objectives and goals for the clients you serve?”). Others used a multi-dimensional conception of the construct, such as Ellett (2000), who identified two aspects of work-related self-efficacy, including belief in one’s ability to perform relevant tasks (task efficacy) and the motivation (motivation efficacy) to exert requisite effort and sedulousness in accomplishing said tasks. Building on this framework, Weaver et al. (2007) divided task efficacy into two facets: practice-oriented competence (i.e., working directly with clients) and agency-related competence (i.e., navigating organizational bureaucracy and politics). In another example, Madden et al. (2014) created a composite variable by asking respondents about specific practice-oriented skills, such

as “I am capable of assessing sexual abuse cases,” “I am capable of assessing physical abuse cases,” “I am capable of assessing neglect cases,” and “I am capable of assessing domestic violence cases.”

Of the 13 empirical studies pertaining to the relation between work-related self-efficacy and turnover or related outcomes identified in this review, five contained non-significant findings, including Weaver et al. (2007), who studied both actual turnover and turnover intent, Dickinson and Painter (2009) (actual turnover), Madden et al. (2014) (employment duration), McCrae et al. (2015) (turnover intentions), and Benton (2016) (actual turnover). On the other hand, Jones and Okamura (2000) found self-perceived competency was associated with retention in the agency, although this finding is only suggestive since it was obtained using bivariate methods, which are unable to control for confounds. Ellett (2007), who also used bivariate methods, found efficacy for work tasks modestly correlated with intent to remain employed ($r = .17$) while motivation efficacy’s correlation with intent to remain was somewhat stronger ($r = .32$), although these results were also substantiated in a multivariate study of the same sample (Ellett, 2000), and using qualitative methods with a different sample (Ellett et al., 2007). In the qualitative study, two of the themes that emerged under the category of personal factors contributing to employee retention were “requisite knowledge, skills, abilities, self-efficacy, and dispositions for child welfare work” and “personal and professional commitment to child welfare and clients, and a desire to make a difference” (Ellett et al., 2007, p. 274), which closely mirror task efficacy and motivation efficacy, respectively. Finally, Chen and Scannapieco (2010), Lee et al. (2011b), and Middleton (2011) found higher work-related self-efficacy was significantly associated with lower turnover intentions.

Unlike these studies, Dickinson and Painter (2009) found increased self-efficacy was predictive of higher turnover intent. The authors speculated workers with higher perceived self-efficacy might feel more confident in their ability to find other employment. This finding indicates the relation of work-related self-efficacy and turnover is probably contingent on other factors. For instance, results from Rao Hermon et al. (2018) revealed Title IV-E trained respondents who left the study agency had lower self-efficacy scores than non-Title IV-E leavers, although a substantive interpretation of this finding was not provided. Taken together, these findings indicate Title IV-E training could moderate the association between work-related self-efficacy and turnover.

There is only one study identified in this review, Potter et al. (2009), that included an assessment of the relation between work-related self-efficacy and job satisfaction. In both waves of this mixed methods study, worker perceptions of preparedness for PCW practice significantly and positively predicted job satisfaction. However, self-assessment of casework skills was not related to job satisfaction in either wave. The authors did not offer an interpretation or analysis of this particular aspect of their findings.

Compensation.

Researchers have measured compensation in a variety of ways, including actual compensation (e.g., Benton, 2016; Dickinson & Perry, 2003; Hwang & Hopkins, 2012; Shim, 2010) and satisfaction with compensation (all other studies identified below). Sample items used to measure compensation satisfaction include “I feel I am being paid a fair amount for the work I do,” “I feel satisfied with my chances for salary increases” (Auerbach et al., 2010), “My pay is good considering what others in this area are paid,” “The benefits for my job are good” (Lambert

et al., 2012), or “I am paid fairly considering the responsibilities that I have” (Dickinson & Painter, 2009).

Qualitative findings by Ellett et al. (2007, p. 273) indicated salaries contribute to turnover when they “are not competitive with other social and human service agencies, and comparable professions (e.g., teaching, nursing).” Similarly, results of a another qualitative inquiry by Leung et al. (2010) indicated low pay is an important contributing factor in turnover. Of 20 empirical studies identified in this review, 11 contained non-significant findings for relations between compensation and turnover or related constructs, including actual turnover (Benton, 2016; Dickinson & Painter, 2009; Smith, 2005; Smith & Clark, 2011; Yankeelov et al., 2009), employment duration (Madden et al., 2014), and turnover intentions (Auerbach et al., 2010; Dickinson & Painter, 2009; McGowan et al., 2009; Mor Barak et al., 2006; Strolin-Goltzman, 2008; Strolin-Goltzman et al., 2007). On the other hand, authors of eight studies reported greater compensation or satisfaction with compensation relating to lower turnover (Dickinson & Perry, 2003) or turnover intent (Chen, Park, & Park, 2012; Collins-Camargo et al., 2012; Hwang & Hopkins, 2012; Jayaratne & Chess, 1984; Lambert et al., 2012; Lambert et al., 2001; Shim, 2010).

Mixed findings by Jones and Okamura (2000) are particularly interesting for the present study. In their study, dissatisfaction with salary meant remaining with the agency for a shorter time, but only for Title IV-E non-recipients. Although this study only employed bivariate methods and the authors did not formally test for an interaction effect, these results suggest compensation’s salience in terms of retention could be different among Title IV-E stipend recipients and non-recipients, respectively.

Five studies investigated the relation between compensation and job satisfaction. Of these, two reported non-significant findings, including one measuring satisfaction with income (Jayaratne & Chess, 1984) and another measuring actual income (Barth et al., 2008). Conversely, Lambert et al. (2001) and Schweitzer et al. (2013) found salary satisfaction positively predicted job satisfaction. Mor Barak et al. (2006) took a more nuanced view of salary satisfaction, including measures of perceived fairness of both (a) the processes organizations use to allocate rewards and compensation (procedural justice) and (b) actual compensation (distributive justice). Using path analysis, the researchers determined distributive justice positively predicted job satisfaction but procedural justice was non-significant. None of these studies included an indicator for Title IV-E stipend status.

Position/job type.

A less investigated aspect of PCW turnover is the role of position or job type. Position is analyzed primarily as a comparison between front-line workers and supervisors/managers. Results from several prior studies indicate position could have an important influence on turnover in PCW. For example, in a study of urban PCW workers with a wide variety of experience (ranging from new hires to 35 years), Nissly et al. (2005) reported supervisors and managers expressed lower turnover intent vis-à-vis frontline workers. In a sample from a different region of the U.S. that included both urban and rural workers, McGowan et al. (2009) found supervisors expressed slightly lower turnover intentions, and in yet another separate sample, Lambert et al. (2012) also found lower turnover intentions among supervisors. When comparing clinical PCW professionals and managers/administrators, Claiborne et al. (2015) found different patterns among antecedents such as role overload and supervisor support and job

search behaviors, revealing different job aspects are relevant to turnover intentions for workers at various levels of an organization.

Nevertheless, as with other antecedents of turnover and related outcomes discussed in this review, the evidence regarding the influence of position is not settled. For instance, contrary to other studies reported above, findings from Mor Barak et al. (2006) indicated managers expressed higher turnover intentions indirectly through job satisfaction, indicating possible presence of a mediating effect. Similarly, in contrast with Claiborne et al. (2015), qualitative findings by Johnco et al. (2014) did not reveal large differences among case managers (front-line workers), supervisors, and management in terms of factors contributing to retention. Moreover, several studies contained non-significant findings, including outcomes such as organizational commitment (Lambert et al., 2012), job and work withdrawal (Cohen-Callow et al., 2009), and turnover intent (Deglau et al., 2018). Chenot et al. (2009) found frontline workers expressed lower turnover intentions than supervisors only at mid-career, indicating employment duration could moderate the relation between position and turnover.

Six studies linking position/job type and job satisfaction were identified in this review. While Barth et al. (2008) found no significant difference in job satisfaction comparing intake versus direct service workers, and there was no difference in job satisfaction when comparing supervisors with direct service workers in a study by Lambert et al. (2012), bivariate results from Landsman (2002) indicated direct service workers had lower job satisfaction compared with all other workers, including supervisors, administrators, and others. Lambert et al. did not offer an explanation, instead merely noting the significant correlation meant position would be included as a covariate in subsequent multivariate analyses. On the other hand, Mor Barak et al.'s (2006) findings indicated managers reported lower job satisfaction vis-à-vis direct service providers.

Once again, no explanation was offered regarding these findings. Meanwhile, Strand and Dore (2009) differentiated among three organizational levels, determining managers had the highest satisfaction, followed by direct service workers then supervisors. They concluded agencies might “might focus on supervision, explore for the meaning of dissatisfaction with co-workers, and develop strategies to improve communication and operating conditions” (Strand & Dore, 2009, p. 395).

For the purposes of the present inquiry, probably the most important study assessing the relation of position/job type and job satisfaction was by Lizano and Mor Barak (2015). As previously mentioned, this study involved a multi-group path model, comparing workers who participated in a Title IV-E MSW program with those who had not. Results indicated direct service workers’ job satisfaction was lower than supervisors, but only among Title IV-E MSW recipients. The authors concluded “This finding suggests that specially trained child welfare workers may be more satisfied in supervisory or management positions than working in direct service provision” (Lizano & Mor Barak, 2015, p. 25). The important point is this result shows the factors potentially driving job satisfaction may differ among those PCW workers who received Title IV-E training stipends and those who did not, which is a basic premise of the current study.

The Lizano and Mor Barak (2015) study was also important from a methodological standpoint, because it demonstrated receipt of Title IV-E stipends truly moderated the relation of position/job type and job satisfaction rather than merely showing the regression path was significant in one group but not the other. This latter approach does not provide evidence of a moderation effect; instead, this can only be demonstrated by checking for a significant difference in regression parameter estimates across groups, as Lizano and Mor Barak (2015) did. This

methodological aspect of multi-group analysis is discussed further subsequently in this chapter as well as Chapter 3.

Job satisfaction.

As Spector (1985, p. 695) stated, “job satisfaction is typically referred to as an emotional-affective response to a job or specific aspects of a job.” As such, prior researchers have taken one of two basic approaches to operationalizing job satisfaction: omnibus measures of overall job satisfaction or multi-faceted instruments that delve into various job aspects. For instance Weaver et al. (2007) used 22 items from Spector’s (1985) Job Satisfaction Survey, which taps nine dimensions of job satisfaction, including pay, promotion, supervision, benefits, etc. Meanwhile, other researchers measured overall job satisfaction with a single question, a set of related questions (e.g., Landsman, 2001), or total scores summed from subscales that tapped specific facets of job satisfaction (e.g., Cohen-Callow et al., 2009).

As discussed in Chapter 1, Landsman’s (2001) study served as the primary foundation of the conceptual framework depicted in Figures 1 and 2. In the Landsman study, job satisfaction mediated relations between antecedents such as supervisor support, role overload, and promotional opportunity and outcomes like organizational commitment and turnover intentions. Therefore, it is important to review prior empirical studies linking job satisfaction and turnover-related outcomes, including job satisfaction’s role as a mediator of distal causes of turnover. In this review, 23 empirical studies linking job satisfaction and turnover-related outcomes were identified. An additional five studies (Aarons et al., 2009; Augsberger et al., 2012; Chen & Scannapieco, 2010; Hopkins et al., 2010; McGowan et al., 2009) were excluded since job satisfaction was mixed with other constructs (e.g., work-related self-efficacy, organizational commitment).

While authors of five studies (Benton, 2016; Cohen-Callow et al., 2009; Dickinson & Perry, 2003; Madden et al., 2014; Weaver et al., 2007) reported non-significant findings, Jones and Okamura (2000), Cahalane and Sites (2008), O'Donnell and Kirkner (2009a), Faller, Grabarek, and Ortega (2010), and Rao Hermon et al. (2018) all linked higher job satisfaction with increased retention. Similarly, Landsman (2001), Lambert et al. (2001), Mor Barak et al. (2006), Weaver et al. (2007), Strolin-Goltzman et al. (2007), Barbee et al. (2009a), Potter et al. (2009), Auerbach et al. (2010), Brimhall et al. (2014), Hwang and Hopkins (2015), Boyas et al. (2015), and McCrae et al. (2015) found higher job satisfaction was associated with lower turnover intentions. Finally, higher job satisfaction has also been linked to lower expressions of job withdrawal (Cohen-Callow et al., 2009) and job search behaviors (Zeitlin, Augsberger, Auerbach, & McGowan, 2014) and higher expressions of organizational commitment (Lambert et al., 2012; Landsman, 2001).

In addition to these findings, several other studies provided empirical support for the mediating role of job satisfaction. Findings from Lambert et al. (2001) and Lambert et al. (2012) suggest job satisfaction, together with organizational commitment, mediate the influence of job characteristics (e.g., role overload, quality of supervision, coworker relations) and personal characteristics (e.g., demographic variables, position/job type) on turnover intent. Similarly, Brimhall et al. (2014) found job satisfaction, along with organizational climate, mediates the influence of individual characteristics (e.g., demographic variables, position/job type) and work context (e.g., relations with supervisor) on turnover intentions. In a study by Mor Barak et al. (2006), job satisfaction mediated the relation of position/job type and turnover intentions.

Demographic characteristics.

In addition to individual attitudes and job characteristics, some researchers hypothesize demographic factors, such as geographic location, age, race/ethnicity, and gender, could influence PCW turnover. Many researchers exclude such indicators from their models, either implicitly or explicitly assuming they play no role in turnover dynamics. Omission of relevant indicators — even ones that are not substantively interesting — could bias estimates for other variables (Berry, 1993). Of 66 turnover-related empirical studies identified in this review, 28 did not include race/ethnicity, age, or sex as a covariate or explanatory variable. Similarly, even though unemployment and poverty rates vary by location, and these factors “may affect the employment-related behaviors of public child welfare social workers through their relationships with child maltreatment rates in the populations they serve” (Fulcher & Smith, 2010, p. 447), sparse prior empirical research is available regarding the role rural/urban location might play in PCW turnover. In terms of job satisfaction, out of 16 studies 10 included at least one indicator of demographic characteristics (i.e., race, age, gender). The following paragraphs contain a discussion of findings related to demographic variables.

Rural/urban location.

Of the nine studies that included measures of rural/urban location, two of these (Landsman, 2002; Shim, 2010) contained non-significant findings. Although Shim (2010) hypothesized urban workers would express higher turnover intentions owing to ample job options, the data did not support this notion. Moreover, Landsman (2002) noted the relation between urban/rural location and turnover intent was non-significant after controlling for employee position and agency size. However, a study by Collins-Camargo et al. (2012) provided evidence turnover intent is lower among rural PCW workers, although they did not offer any

explanation for this finding. Results by Yankeelov et al. (2009) further substantiated Collins-Camargo et al.'s findings, but in both cases bivariate techniques were used, meaning confounds could not be controlled. The findings are, therefore, suggestive. However, a study by Griffiths et al. (2017), which did include individual characteristics such as workload and quality of supervision, also indicated urban workers had higher turnover intent. In contrast, Fulcher and Smith (2010) found just the opposite: in a study of PCW workers in California, rural counties had higher turnover rates than urban counties, and rurality was a more important predictor than other environmental variables, such as unemployment rate. However, the unit of analysis in this study was counties, and no individual worker characteristics (e.g., job satisfaction, social integration) were accounted for.

As discussed earlier in the chapter, rural/urban location not only can have a direct influence on job satisfaction, turnover intent, and related constructs, but it can also moderate the influence of other antecedents. Strolin-Goltzman et al. (2006) called for additional research into rural/urban location serving as a moderator of other antecedents of turnover, and three such studies were identified in this review. As previously discussed, Strolin-Goltzman et al. (2007) found more experienced workers expressed lower turnover intentions and holders of an MSW degree expressed higher turnover intentions, but these associations were only significant among urban workers (who presumably had more opportunities for other employment). Similarly, McGowan et al. (2009) also found employment longevity was associated with lower turnover intent, but only for urban workers. Meanwhile, Kim and Hopkins (2017) found social integration positively related to organizational commitment, but only for rural workers, while older age predicted higher organizational commitment, but only among urban respondents. None of the studies that included rural/urban location accounted for Title IV-E status.

Only three studies identified in this review specifically ascertained the influence of rural/urban location on job satisfaction. Landsman (2002) regressed several outcomes, including job satisfaction, on organizational size (i.e., number of CW positions in the agency), rurality, and the joint effect of organizational size and rurality. Although the zero-order correlation of rurality (measured on a nine-point continuum) and job satisfaction was significant ($r = .12$), the association was non-significant after controlling organization size. Furthermore, rurality and organization size together only explained about 2% of the variation in job satisfaction. The relation between rural/urban location and job satisfaction was also non-significant in a study by Glisson et al. (2012), where the indicator was included only as a covariate. Conversely, using a nationally-representative sample Barth et al. (2008) found non-urban workers had higher job satisfaction, although they also noted the relatively small portion of variance explained.

Kim and Hopkins (2017) constructed two separate multiple regression models for the rural and urban workers in their sample in order to determine if the pattern of significant findings was different in each group. While a few variables were significantly related to job satisfaction in only in one group (e.g., race, social integration, MSW status), these results are only suggestive of rural/urban location's role as a moderator variable since they did not test if the regression slope parameter estimates were significantly different across groups. Nevertheless, the authors concluded different workplace factors were salient to urban and rural workers, respectively, indicating managers should tailor interventions designed to increase job satisfaction based on workplace location.

Race/ethnicity.

Some investigators have included measures of race or ethnicity (often white versus non-white) in models of PCW turnover. In 22 of these studies, these measures were not significantly

related to turnover. In studies where a significant association was found, substantive interpretation is not always provided since inclusion of a race/ethnicity indicator is often solely for statistical control. For example, results from Hwang and Hopkins (2012) indicated minority PCW workers expressed higher turnover intention, but the authors stipulated minority status as only a covariate, and they offered no explanation for the finding. However, there is some evidence race/ethnicity can play a meaningful role in PCW turnover.

Hopkins et al. (2010) found non-white employees expressed higher levels of job search behaviors and job withdrawal. The authors noted race/ethnicity might not have been the salient factor per se, but that non-white employees in their sample were disproportionately represented in urban areas “where morale was reported to be the lowest and safety concerns the highest” (p. 1386). Griffiths et al. (2017) also found non-white workers expressed higher turnover intent, but these researchers also controlled for rural/urban location, unlike Hopkins et al. (2010). Another important difference between the two studies is the authors’ interpretations of the effect of being in an urban area. While Hopkins et al. (2010) speculated poor working conditions in urban areas could lead non-white workers to intend to leave, Griffiths et al. (2017) offered an alternative postulation, that urban areas have a higher number of social service agencies, thereby offering more employment options and subsequently diminishing remain intentions. Mor Barak et al. (2001) and Mor Barak et al. (2006), on the other hand, suggested demographic characteristics influence turnover intention indirectly. For example, if workers who are ethnic minorities perceive unfair treatment at work, it could lead to lower job satisfaction, and ultimately higher turnover intent.

Faller et al. (2010) offered yet another perspective. In their study, they found non-white workers to be less committed to remaining at their specific agencies and to remaining in the child

welfare field, although race/ethnicity was not significantly related to actual turnover. The authors speculated non-white workers might feel discriminated against in the general workforce, and so may therefore perceive fewer employment alternatives even while not being highly committed to PCW work, or that they may feel discontent toward agencies because of perceived discriminatory practices toward system-involved children and families of color. Regardless, the authors concluded more research is necessary to understand the reasons why non-white workers express lower commitment to PCW.

Despite these findings that non-white workers tend to express higher turnover intent, Jones and Okamura (2000), Landsman (2001), and Shim (2010) all found turnover or turnover intent was lower for non-white workers. However, in Jones and Okamura's (2000) retention study, time since date of hire to the end of the study (when retention was determined) was not controlled, and the authors noted non-white workers were the most recently hired. As with Hwang and Hopkins (2012) discussed previously, race/ethnicity was included only as a control variable in Landsman's (2001) and Shim's (2010) study, so no substantive explanations about the findings were offered.

As discussed in the previous sub-section, Kim and Hopkins (2017) split their sample into rural and urban groups and conducted two separate regression models, although they did not formally test for group-based interactions, and they did not control for Title IV-E status. Contrary to Glisson et al. (2012) and Lizano and Mor Barak (2015), they reported White respondents in urban locations had higher job satisfaction than non-White respondents, although the relation was non-significant for rural workers. As with the other authors, Kim and Hopkins (2017) did not offer a substantive explanation of their findings.

In studies by Landsman (2001), Barth et al. (2008), Strand and Dore (2009), and Lambert et al. (2012), there was no significant association between minority status and job satisfaction. Conversely, in a nationally-representative sample Glisson et al. (2012) reported African-Americans and Hispanic respondents indicated higher job satisfaction than their White counterparts, even after controlling for rural/urban location. However, this study did not control for Title IV-E stipend receipt, whereas Lizano and Mor Barak (2015) found non-White respondents had higher job satisfaction, but only for the group that received specialized PCW training (Title IV-E stipends). However, these findings are only suggestive for two reasons. Firstly, the sample consisted entirely of urban workers, and secondly the difference in regression parameter estimates across the two groups did not achieve statistical significance, indicating receipt of specialized PCW training did not truly moderate the association between race/ethnicity and job satisfaction.

Age.

Although age was non-significant in 13 studies, Landsman (2001), Nissly et al. (2005), Shim (2010), Hwang and Hopkins (2012), Kruzich et al. (2014), Griffiths et al. (2017), and Deglau et al. (2018) found a significant, inverse relation between worker age and turnover intent. Similarly, other investigators have found higher worker age to be associated with longer employment duration (Aarons et al., 2009), lower risk of quitting (Dickinson & Painter, 2009), and lower work withdrawal (Hopkins et al., 2010). In these studies, worker age was considered a control variable, and therefore the authors offered no substantive explanation of significant findings.

Other researchers did offer substantive interpretations, hypothesizing worker age is an important influence on PCW turnover and related constructs, either directly or as a moderating

effect on other influences. Mor Barak et al. (2006, p. 566) found younger workers were “less vested in the organization,” and therefore tended to express higher turnover intent. While Lambert et al. (2012) also found older workers were less likely to express a desire to leave, they distinguished between age and employment duration, as both variables were significantly and inversely related to turnover intentions. The authors speculated older workers may perceive fewer employment alternatives, owing to age discrimination, while employees with longer employment duration may, as Mor Barak et al. (2006) stated, feel more invested in the organization, thereby perceiving higher costs associated with leaving. Boyas et al. (2011, p. 58) echoed both of these explanations, stating “the stronger social bond and ties with the organization [may] create a safeguard against adverse work-related outcomes, such as intent to leave.” Boyas et al. (2015) also reported younger workers expressed higher turnover intentions, suggesting the need for agency managers to develop retention-oriented interventions specifically tailored for younger workers, although the authors did not specify what form(s) such an intervention might take.

As with rural/urban location, worker age may be involved in interaction effects with other antecedents of turnover. For example, Kim and Hopkins (2017) found older age was associated with higher organizational commitment, but only for urban sample. In a study by Curry et al. (2005), higher age was associated with lower odds of leaving, but only for low experience workers (i.e., four or fewer years of service). Conversely, Boyas et al. (2013) reported older workers expressed higher organizational commitment, but only for workers with at least three years’ experience.

Of eight studies that included measures of association between worker age and job satisfaction, five contained non-significant findings (Glisson et al., 2012; Kim & Hopkins, 2017;

Lizano & Mor Barak, 2015; Mor Barak et al., 2006; Strand & Dore, 2009). On the other hand, significant findings were reported in the other three studies (Jayaratne & Chess, 1984; Lambert et al., 2012; Lambert et al., 2001), with older workers indicating higher job satisfaction in each case. None of the authors offered substantive remarks concerning the relation between age and job satisfaction, although all studies but three (Glisson et al., 2012; Jayaratne & Chess, 1984; Kim & Hopkins, 2017) controlled for employment duration.

Gender.

Unlike other antecedents discussed in this review, despite being non-significant in 22 of 28 studies, prior research into the relations between gender (i.e., binary male/female indicator) and turnover-related outcomes is relatively clear and straightforward. In terms of turnover intentions (Deglau et al., 2018; Landsman, 2001; Shim, 2010), actual turnover (Curry et al., 2005; Rosenthal & Waters, 2006; Weaver et al., 2007), work withdrawal (Hopkins et al., 2010), and employment duration (Madden et al., 2014), outcomes for male workers are consistently in the direction of higher propensity for leaving PCW. Save for one, in all the forgoing studies the authors included gender solely as a covariate and offered no substantive explanations regarding the significant findings. However, Madden et al. (2014) did present a discussion about dynamics surrounding male PCW workers. These authors noted while males in the helping professions, including PCW, can sometimes enjoy greater upward mobility vis-à-vis their female colleagues, they can also be faced with skepticism about their “motivations for working with women and children” (Madden et al., 2014, p. 41), and because society broadly considers and expects PCW to be a female-dominated field.

Eight studies of job satisfaction included gender, six of which reported non-significant results (Barth et al., 2008; Glisson et al., 2012; Kim & Hopkins, 2017; Lambert et al., 2012; Mor

Barak et al., 2006; Strand & Dore, 2009). Barth et al. (2008), who used a nationally-representative sample, noted non-significant findings could result from relatively low numbers of male PCW workers combined with the fact that the most dissatisfied workers likely already left the field, thus yielding low statistical power. Two studies (Lambert et al., 2001; Landsman, 2001) reported males have lower job satisfaction. Lambert et al. (2001) explained their results might be attributed to broader societal pressures for men to serve as primary breadwinners, meaning men are more likely to remain with jobs they are not satisfied with. However, this study used a nationally-representative sample of workers, not limited to PCW. In Landsman's (2001) study, which was limited to PCW employees, male respondents also expressed lower job satisfaction, although no substantive explanation was offered since the indicator served only as a covariate.

Limitations of prior work.

As is evident from the foregoing review, empirical results are quite mixed regarding the antecedents of turnover and related constructs. One possible reason for indeterminate or even contradictory findings is the pervasiveness of methodological deficiencies. This section presents a brief overview of the departures from modern best practices found in the reviewed articles. Note the methodological approach for the present study, outlined in Chapter 3, addresses the shortcomings discussed below.

Catch-all constructs.

Several studies contained composite constructs that were a combination of related but distinct variables, which complicates interpretation and could result in mixed findings. For example, several results from Augsberger et al. (2012) were excluded from this literature review because measures of salary satisfaction, professional development, social integration, and job

satisfaction were aggregated, along with other measures, into a composite construct called job respect. Note this was done without the benefit of a factor analysis, which could have helped determine if grouping these constructs together under a single construct was consistent with the pattern of responses; instead, unidimensionality of the factor structure was simply assumed. Similarly, some results from Chen and Scannapieco (2010) were excluded because they collapsed many constructs (e.g., salary satisfaction, workload, professional development, social integration) into a single dimension called job satisfaction, again without the benefit of a factor analysis.

As Kline (2016) stated, using “average or total scores over sets of items . . . can mask the true absence of unidimensionality and distort the results” (p. 458). Said another way, without first checking the psychometric properties of summed/averaged items, researchers could be combining items that do not measure the same construct. This, in turn, leads to the so-called jingle-jangle fallacy, wherein researchers assume items measure constructs for which they are named, rather than actually checking the reasonableness of this assumption. In these cases, it is simply not known what has been measured, so any claims made on the basis of model results are dubious.

Omitting interaction effects.

An important part of this literature review is examining evidence supporting interaction effects among antecedents of turnover and job satisfaction. For example, content analysis of open ended questions by Willis et al. (2016b) revealed factors driving turnover could be different for Title IV-E recipients and non-recipients, but the authors noted their approach could not determine whether such differences are statistically significant. Nevertheless, of the 71 quantitative articles identified in this review, only 14 included some type of interaction effect,

either formally tested or merely suggestive, despite several qualitative studies that are suggestive of an interaction effect.

Omitting interaction effects (i.e., when the influence of one X variable depends upon the value of another X variable) is a type of specification error, which can lead to biased parameter estimates (Berry, 1993). The PCW turnover literature is very limited in terms of interaction effects that might bear upon job satisfaction, turnover intent, or related constructs, which probably goes a long way toward explaining the pervasiveness of mixed results. Consider a simple example to illustrate this point. Suppose a researcher theorizes turnover intent is a function of satisfaction with salary (measured on an interval scale) and Title IV-E stipend status (measured with a dummy variable). This model can be expressed using the Equation 1 below; let X_1 represent salary satisfaction and X_2 represent Title IV-E stipend status:

$$\text{Turnover Intent} = a + b_1X_1 + b_2X_2 + e \quad \text{EQ 1}$$

In this specification, b_1 represents the partial effect of salary satisfaction on turnover intent while b_2 represents the partial effect of Title IV-E stipend status. Without an interaction effect (i.e., $b_3X_1X_2$), the partial effect of salary satisfaction is held constant across both levels of X_2 . Said another way, this specification forces a single estimate of the influence of salary satisfaction on turnover intention, and this estimate is not allowed to vary across groups. Assuming there is a difference in the influence of salary satisfaction for Title IV-E recipients versus non-recipients, omission of the X_1X_2 interaction effect in Equation 1 would lead to two problems. First, the estimate of b_1 would be biased, so incorrect inferences about the influence of salary satisfaction would likely be drawn. Second, an important group difference when comparing Title IV-E recipients and non-recipients would go undetected.

Improper multiple samples procedures.

As mentioned above, several authors (Barbee et al., 2018; Boyas et al., 2011; Boyas et al., 2013; Chenot et al., 2009; Curry et al., 2005; Kim & Hopkins, 2017) split their samples according to some criterion (e.g., years of service, rural/urban, receipt of specialized PCW training) and conducted separate multiple regression models or path models for each group. However, only one study (Lizano & Mor Barak, 2015) incorporated proper procedures for testing moderation of the grouping variable. In most cases, researchers assumed the groups were different if a particular regression parameter was statistically significant in one group but not the other. However, this does not indicate the difference between the groups' regression parameter estimates is statistically significant (Gelman & Stern, 2006), and therefore is not indicative of a statistically significant interaction effect.

Consider a simple extension of the example used in Equation 1 to illustrate this point. To determine if the influence of salary satisfaction (X_1) on turnover intent is different for Title IV-E recipients and non-recipients (X_2), one possible approach would be inclusion of an interaction term:

$$\text{Turnover Intent} = a + b_1X_1 + b_2X_2 + b_3X_1X_2 + e \quad \text{EQ 2}$$

Alternatively, a multiple-sample approach could be used, which involves splitting the sample into two groups (Title IV-E recipients and non-recipients) and computing estimates for the following regression model separately for each group (subscript 0 indicates non-recipient while subscript 1 indicates recipient):

$$\text{Turnover Intent}_0 = a_0 + b_{10}X_{10} + e_0 \quad \text{EQ 2.1}$$

$$\text{Turnover Intent}_1 = a_1 + b_{11}X_{11} + e_1 \quad \text{EQ 2.2}$$

In the multiple group approach, notice separate intercepts (a), regression parameters (b), and error terms (e) are calculated for each group. Suppose b_{10} achieves significance for the non-recipient group but b_{11} does not achieve significance for the stipend recipient group. This alone is insufficient evidence to claim group membership moderates the association of salary satisfaction and turnover intent. To make this claim, it is necessary to show that the difference between b_{10} and b_{11} is not zero, after accounting for sampling error, as shown in Equation 3:

$$b_{10} - b_{11} \neq 0 \quad \text{EQ 3}$$

Polychotomizing continuous or interval data.

Several authors dichotomized or polychotomized continuous or interval data, which discards information and tends to downwardly bias the estimated strength of association between variables (Thompson, 2006). For instance, Griffiths et al. (2017) and Deglau et al. (2018) trichotomized a continuous measure of turnover intent. Chen and Scannapieco (2010) dichotomized several continuous predictors, presumably (and unnecessarily) to fit the analysis into an ANOVA framework. Similarly, Ellett (2009) dichotomized a continuous measure of turnover intentions, retaining only the upper and lower quartiles for the analysis (i.e., the middle 50% of respondents were deleted). Presumably this was done to fit the analysis into a discriminant function analysis (DFA) framework, although structural equation modeling (SEM) would have been more appropriate. To check worker age as a potential moderator, Boyas et al. (2011) performed a mean split of their sample based on age and performed a two-group path model. Not only did this practice dichotomize a continuous variable, but this was done in a way that depended upon the sample mean. However, testing the significance of interaction effects at specific values of a moderator based on sample statistics introduces uncertainty (since the sample mean would vary from sample to sample), thereby potentially inflating type I error rates (Liu,

West, Levy, & Aiken, 2017). Curry et al. (2005) and Chenot et al. (2009) did something similar, polychotomizing years of service at arbitrary values and performing separate regression analyses for each group.

Improper model building and selection.

Dickinson and Perry (2003) and McCrae et al. (2015) reported the common practice of using bivariate relations to screen for variables to include in multivariate procedures. However, it is possible for significant association to emerge only when other pertinent variables are controlled for (a phenomenon known as suppressor effects), meaning important variables could be excluded from subsequent multivariate models (Pandey & Elliott, 2010). Use of statistical regression methods (i.e., forward, backward, stepwise) can also result in excluding important variables from a model because of suppressor effects, and they can also result in over-fitting a model to a specific sample, which is unlikely to generalize to other research settings (Tabachnick & Fidell, 2013). Several authors reported using such techniques, including Ellett (2000), Dickinson and Perry (2003), Jacquet et al. (2008), and Cohen-Callow et al. (2009). Besides producing idiosyncratic models that are unlikely to be replicated in other samples, statistical regression methods focus on prediction rather than explanation of underlying phenomena. As Asher (1983, p. 11) cautioned, “one should not allow the testing and revising of models to become an enterprise completely determined by statistical results devoid of theoretical underpinnings.”

There were also some weaknesses in terms of constructing and reporting models involving mediated (indirect) paths. Boyas et al. (2011) did not follow best practices in building a parsimonious path model of turnover intentions. They did not perform statistical tests to ensure model fit was not significantly worsened after dropping non-significant paths (Kline, 2016).

Similarly, Lambert et al. (2001) and Lambert et al. (2012) did not statistically test whether regression parameter estimates for omitted paths were equal to zero; rather, the authors just assumed the paths were non-significant. The authors also did not perform any significance test for the indirect path, and no mediation effect size was offered. These oversights greatly diminish the strength of their claims for indirect effects. Neither did Landsman (2001) check significance of indirect paths or provide effect sizes of mediation.

Lack of control variables.

As previously discussed, very few studies (10) controlled for receipt of Title IV-E training stipends. In addition, there were nine studies whose samples comprised entirely of Title IV-E stipend recipients, making comparisons with non-recipients impossible. Beyond this, 29 studies provided no control for workers' demographic characteristics (i.e., age, race/ethnicity, gender), despite previously outlined empirical findings that demonstrated there is often a significant association between demographic attributes and turnover or related constructs. Finally, seven studies employed bivariate approaches, meaning there were no statistical controls at all. When relevant confounding factors are not controlled, statistical results could be misleading or entirely invalid. More robust models that control for known or potential confounds are needed to advance the literature on PCW turnover. More inclusive, multivariate models will also help determine the unique influence of various antecedents of PCW job satisfaction and turnover intentions.

Missing data handling.

While many authors did not explicitly state how they handled missing data (an issue in itself that should be addressed), several listed approaches that are common, but outdated. For example, Griffiths et al. (2017) used listwise deletion, which discards information and produces

more biased parameter estimates and larger standard errors vis-à-vis a modern approach such as full information maximum likelihood (FIML) (Enders, 2010). Jacquet et al. (2008) Benton (2016) used mean replacement, which “severely distorts the resulting parameter estimates,” even under the best case scenario of data missing completely at random (Enders, 2010, p. 42).

Summary

There is a body of suggestive evidence that Title IV-E training could be beneficial for retention, and that different factors are salient for turnover intentions among Title IV-E-trained workers. However, these results are far from definitive. As the foregoing literature review laid bare, the phenomenon of turnover intent formation in PCW is contingent and complex, yet most of the statistical models employed in prior empirical literature are unrealistically simple. Given this state of affairs, it is unsurprising empirical results regarding the relation between Title IV-E training and PCW turnover are not clear. In addition to not having robustly demonstrated Title IV-E training boosts retention, prior research has also not revealed the mechanisms or linkages how this would occur, if it were true. What is needed is a more comprehensive model of turnover intention, with the ability to compare Title IV-E recipients and non-recipients. The current study is designed to fill this important research gap.

The goal of this study is to investigate how Title IV-E may modify the associations among working environment, worker characteristics, and turnover intentions. A conceptual framework was adapted where worker characteristics and attitudes were conceptualized as distal antecedents, and these variables influence turnover intent via job satisfaction. In other words, it is asserted that job satisfaction mediates the associations between distal antecedents and the outcome—turnover intent. To investigate the moderation effect of Title IV-E, the conceptual framework was further extended by adopting a two-group approach. Two-group comparison

enables the investigator to compare the direction and magnitude of the influence of an antecedent on turnover intent between Title IV-E recipients and non-recipients.

Based on the conceptual framework, the investigator performed an extensive literature review on the relations between variables of individual worker attitudes and characteristics (listed in the conceptual framework) and turnover-related constructs as well as the mediation effect of job satisfaction. Overall, the findings revealed the influence of the antecedents on turnover is complicated and nuanced. It is common to see that two variables have a joint effect on turnover intent or job satisfaction (e.g., age and rural/urban location, social integration and employment duration, etc.). Another common theme in this review is the pervasiveness of methodological weaknesses, including omission of important interaction effects and control variables along with measurement problems such as polychotomizing continuous data and creating composite constructs without statistical justification. Understanding how the process underlying turnover intent might be different among Title IV-E recipients and non-recipients requires more advanced statistical modeling techniques than have been applied to date. As stated in Chapter 1, the benefits of this study include (a) helping identify whether and how Title IV-E stipends help stem PCW turnover and (b) identifying the workplace factors most important for retaining Title IV-E workers, thereby potentially saving money and improving outcomes for system-involved youth and families.

Research Questions and Hypotheses

The central research question of this study is whether receipt of Title IV-E training moderates the process underlying turnover intent. Specifically, are the strengths and patterns of relations between individual worker characteristics and job attitudes on the one hand, and turnover intent on the other, similar across groups defined by Title IV-E training status, and are

these relations equally mediated by job satisfaction? While the literature review did not reveal sufficiently concrete evidence to make specific, directional hypotheses, the investigator hypothesizes Title IV-E stipend status will moderate the presence and/or strength of relations along the mediated path *antecedents* → *job satisfaction* → *turnover intention*. Specifically, the investigator hypothesizes that, for at least some constructs, the path from antecedents to job satisfaction, the path from job satisfaction to turnover intentions, and/or the complete mediated path will be significantly different in magnitude in the Title IV-E group. The non-specific nature of these hypotheses indicates the nature of the present study is exploratory.

Chapter 3: Methods

Sample and Data Collection

The data set used in the present study was part of a larger study; construction of the data set was described by Leung and Willis (2012). Several data sets were provided by DFPS, including information on outcomes for five measures: recurrence of child maltreatment, foster care re-entries, stability of foster care placement, length of time to achieve reunification, and length of time to achieve adoption. A sixth data set was also provided, which contained identifying information pertaining to each worker who contributed to the outcomes recorded in the other five data sets. The sixth data set contained approximately 4.9 million transactions from September 2003 to October 2005. All six data sets were merged to match each worker to the respective outcomes for which they had responsibility. If multiple workers were assigned to the same child, the worker who worked the longest with the child was assigned to the case; in the event of ties, the latest worker was matched with the case. After the matching process, the data set was reduced to about 1.8 million unique transactions.

In 2008, DFPS had 4,078 PCW employees. Due to churn, only 2,303 of these workers were matched with the 4.9 million transactions in the data sets described above. A survey was approved by the University Committee for the Protection of Human Subjects and sent to these 2,303 workers using SurveyMonkey. One hundred and one e-mails were returned as invalid addresses, leaving 2,202 potential respondents. Of these, 1,187 responses were received, for a response rate of 53.9%. After discarding responses that had excessive missing data (i.e., missing all or nearly all Likert response data or missing information on receipt of Title IV-E stipend), 969 cases were available for analysis. Participation in the survey was voluntary and no special incentives were offered. Appendix A presents the survey cover letter.

Measures

The survey questionnaire was developed in consultation with a statewide evaluation committee, including DFPS supervisors and administrators (Willis et al., 2016b). The instrument consisted of 40 items, of which 17 Likert-type items are used in the present study. These items are listed in Appendix B; the labels in parentheses following each item correspond to the construct names shown in Figure 2. The Likert items were measured on a five-point scale; some categories were collapsed due to low cell counts on some items. Some items were reverse scored such that in all cases higher scores indicate a more favorable/positive attitude; reverse scored items are indicated as such in Appendix B.

Single-item measures were used instead of composite variables. Comrey (1988, p. 756) stated items measuring a latent common factor “should represent alternate forms of each other.” Most constructs were measured using single items, and those constructs measured by multiple items are not alternate forms but rather probe differing aspects of the construct. As a double check that the Likert items actually measure separate constructs, the investigator fit a single-factor confirmatory factor analysis (CFA) model. If the single-factor model fits the data poorly, this provides an additional indication the items measure different constructs (i.e., discriminant validity) and modeling may proceed using the items as single indicators of their relevant domains (Kenny, 1979; Kline, 2016).

Dependent Variable #1: Intention to Stay (ITS).

The first of the two dependent variables in this study is turnover intention. Although items 22.4, 22.5, and 22.6 all pertain to turnover intent, they do so in very different ways. One strength of item 22.4 (which asks about workers’ intention to retire with the agency) is that it is the only item that discriminates between undesirable, preventable turnover and retirements

(Collins-Camargo et al., 2012). To wit, items 22.5 and 22.6 ask about plans to leave the job within the next 12 months and future plans to get a different job, respectively. It is easily conceivable that a person about to retire from DFPS could plan to leave the agency and perhaps even obtain different employment within the next year, though clearly this is a completely different scenario than a relative new hire wanting to leave in the same timeframe. Item 22.4 avoids this ambiguity.

The importance of the distinction is illustrated by Strand, Spath, and Bosco-Ruggiero (2010), who conducted a study of personal and agency factors that related to turnover intentions, measured by asking respondents if they planned to leave “in the next 12 months.” However, the format of this question made interpretation of their findings difficult. For example, although they found managers to have higher job satisfaction than frontline workers, counterintuitively managers also expressed higher intent to leave. The authors stated “This finding may be capturing those staff that are older, in management positions and intend to *retire*” (Strand et al., 2010, p. 343 ,emphasis added). Similarly, Collins-Camargo et al. (2012, p. 291) stated the large percentage of their respondents who indicated an intent to leave their agency within two years “did not take into account respondents who might be close to retirement.” Clearly, experienced managers retiring is not example of preventable, undesirable turnover that is the focus of this study. Conceptually, item 22.4 makes this distinction, and is therefore desirable as the measure of ITS. Nevertheless, the investigator will check validity coefficients (i.e., correlations with other study variables) for several different operationalizations of ITS: items 22.4, 22.5, and 22.6 individually and a latent variable using each of these items as indicators.

Dependent Variable #2: Job satisfaction.

The second dependent variable is job satisfaction. Although multi-item, multi-domain (i.e., instruments designed to assess multiple facets or aspects) measures of job satisfaction are available (e.g., Spector, 1985), the present study used a single item, 22.3 to measure job satisfaction. Overall (facet-free) measures of job satisfaction are often more useful than multi-facet measures, depending upon the research question. In the current study, the aim is to determine if overall job satisfaction mediates the influence of distal antecedents of turnover intentions. Therefore, specific facets of job satisfaction are not important in this study. Furthermore, summation of scores on multi-facet measures are not necessarily parallel to overall measures since the multi-facet measures can exclude some aspects of overall job satisfaction (Scarpello & Campbell, 1983).

Wanous, Reichers, and Hudy (1997) used meta-analytic methods to estimate the minimum reliability of single-item job satisfaction measures; estimates ranged from .45 to .69 with an average of .57. They concluded reliability of single-item job satisfaction measures would likely approach .70 under realistic research scenarios. Using a sample of 745 employees of the Texas Department of Human Services, Dolbier, Webster, McCalister, Mallon, and Steinhardt (2005) followed Wanous et al.'s (1997) approach to check reliability and validity of a single-item job satisfaction measure. The researchers concluded the minimum (conservative) reliability estimate of the single-item measure is .73, with a more realistic estimate of .90. They also established the single-item's concurrent validity with a summed, multi-item job satisfaction measure ($r = .82$), convergent validity with supervisor support, coworker support, and positive affectivity ($r_s = .51, .46, \text{ and } .28$, respectively), and discriminant validity with work stress ($r = -$

.35) and negative affectivity ($r = -.23$). Moreover, the single item measure performed as well as the multi-item measure in predicting turnover intentions.

Work-related self-efficacy.

The survey contains five questions regarding work-related self-efficacy: items 27.1, 28, 32, 34, and 36. However, each item addresses a different aspect of work-related self-efficacy. These areas include university preparation for PCW (27.1), casework skills (28), administrative skills (32), skills working with culturally diverse populations (34), and skills working with disabled clients (36). Because these items are not parallel, or alternate forms, there is no reason to believe a single, underlying work-related self-efficacy factor would drive responses to these questions. Therefore, they were modeled as individual items rather than as indicators of a latent variable.

Social integration, role overload, salary satisfaction, and professional development.

Social integration was measured by four items: 25.1 through 25.4; two of these items relate to different aspects of supervisor relations, one pertains to respect from coworkers, and one relates to work unit cohesiveness. Since the literature review indicated supervisor and coworker relations could independently influence job satisfaction and turnover intent, these items were not combined into a composite variable. Items 26.2 and 26.3 measure role overload, but were modeled separately since they are not alternate forms. Finally, salary satisfaction and professional development satisfaction were measured using single items (22.1 and 22.2, respectively).

Employment duration.

Employment duration was a continuous measure of the years of employment in the present agency. Inclusion of this measure accomplishes two objectives. Firstly, it provided a

means to test for the influence of time on job satisfaction and turnover intentions, as well as the interaction of time and several other explanatory factors, as outlined in Table 5. Secondly, it provided a means to control for employment duration, so that the influence of other explanatory variables may be interpreted as being net of employment duration. This provides a means to control for whether a respondent was still within the Title IV-E stipend payback period. A separate binary indicator of payback status was not included because it would be redundant with the continuous measure of employment duration.

Basic Multivariate Assumptions

Descriptive statistics and diagnostic plots from both *Mplus* (Muthén, Muthén, & Asparouhov, 2017) and R (Fox, 2002) were used to assess basic multivariate assumptions, such as plausible values, means, and standard deviations, outliers (univariate and multivariate), normality (univariate and multivariate), nonlinearity, heteroscedasticity, and multicollinearity (Tabachnick & Fidell, 2013). A combination of bootstrapping and robust standard error estimation (discussed in detail later in this chapter) were used to mitigate departures from normality (Muthén et al., 2017; Nevitt & Hancock, 2009).

Model Building Strategy

The main data analysis strategy involves use of multi-group path analysis (i.e., structural equation modeling with manifest variables), implemented using *Mplus*. Structural equation modeling, or SEM, is frequently thought of as a separate statistical technique, lacking in commonality with more traditional inferential procedures such as *t*-tests and analysis of variance. However, all univariate and multivariate inferential statistics (e.g., *t*-test, analysis of variance, multiple regression) may actually be conceptualized as special (i.e., simplified) cases of SEM (Graham, 2008). Said another way, SEM offers the most flexible statistical framework to test

complex hypotheses while making far fewer assumptions than other approaches such as *t*-tests and regression. In short, modeling complex phenomena such as employee turnover require commensurately sophisticated statistical methods, such as SEM.

As discussed in the remaining sections of this chapter, SEM can incorporate multiple explanatory variables to control for confounds, robust estimation to account for departures from normality, sophisticated missing data handling, and mediation and moderation, all within a single model. From a practical standpoint, while it would be theoretically possible to answer the research questions posed in the present study using a multiple regression framework, it would be extremely laborious, involving the estimation of dozens of separate regression models and then using formulas to manually check for the significance of the differences in regression parameters across groups one at a time, using single degree of freedom tests. Missing data handling would also be more cumbersome, and it is not clear how multiple degree of freedom tests (which, as explained in the next chapter, have several advantages over single degree of freedom tests) or bootstrapping estimates of group differences would be implemented. In contrast, SEM subsumes all these features, which are all performed simultaneously in the estimation of a single model.

Structural equation models consist of two parts: a measurement model and a structural model (Bollen, 1989). The measurement model specifies the relations between constructs and their indicators, while the structural model specifies the relations among constructs. In path analysis, all constructs are measured by a single indicator. In multi-group path analysis, the structural model (i.e., the regression slopes between predictors and outcomes) are estimated separately for each group. In this way, across-group comparisons can be made. Figure 2 depicts the path model of the present study.

To arrive at a feasible yet parsimonious model, the model building strategy proceeded in two main steps. First, using multiple regression the investigator tested each hypothesized predictor and interaction effect for both dependent variables: job satisfaction and ITS. These analyses were performed separately for Title IV-E recipients and non-recipients, respectively. Effects that were both non-significant and trivial (i.e., close to zero) in both groups were not included in the final model. Non-significant, non-trivial effects were retained since their omission could bias other parameter estimates (Fox, 2008; Muthén et al., 2017). In the second step, results from the preliminary models informed which variables and interaction effects were included in the path model. Several models were estimated in an iterative fashion, checking for parameter estimates that varied significantly across groups. Simpler models were tested against more complex ones to ensure model fit did not appreciably deteriorate. Using this model building approach (Kline, 2016) helped arrive at the simplest empirically-defensible model that adequately represents the sample data. Achieving a parsimonious model is important for two reasons. Firstly, it aids interpretation of complex phenomena, such as PCW turnover intent. Secondly, estimating fewer parameters increases statistical power available for estimating other parameters in the model.

Model Estimation

Distributions of responses to Likert-type items often do not meet the assumptions of normal theory methods, especially when there are five or fewer response categories or when distributions are very skewed (Kline, 2016). Accordingly, two leading methods of handling non-normality (including ordered categorical data with five or more categories) were used: maximum likelihood with robust standard errors (MLR option in *Mplus*) and nonparametric bootstrapping (Falk, 2018). Robust maximum likelihood is a normal theory method, but with corrected

standard errors and model test statistics (Kline, 2016). Bootstrapping involves re-sampling the data with replacement such that each bootstrap sample has the same n as the overall sample.

Model parameters are estimated for each bootstrap sample, then asymmetric, empirical confidence intervals are built using results from several thousand bootstrap samples (Hesterberg, 2015). Statistical significance is indicated when the 95% bootstrap confidence interval does not include zero. The advantage of using the resampling approach instead of normal theory methods is freedom from distributional assumptions, and the resampling method is generally superior than traditional approaches (e.g., Sobel test) for testing indirect effects (MacKinnon, Fairchild, & Fritz, 2007), especially when the sample size is not large (Preacher, Rucker, & Hayes, 2007). This was an important consideration since the sample size of the Title IV-E recipient group is 263, or about 27% of the total sample. Robust maximum likelihood and resampling methods tend to excel under different circumstances, so reporting them both provides additional certainty about the results (Muthén et al., 2017).

Missing Data Handling

Missing data were handled using missing at random (MAR) maximum likelihood, including bringing covariates into the model (Muthén et al., 2017), or so-called full information maximum likelihood (FIML). MAR indicates missingness on an outcome variable is related to scores on another variable that is included in the model but not to values on the outcome variable itself (Enders, 2010). Although the MAR assumption is not testable, it is more plausible if missingness on a given variable is related to scores on other variables in the model. Correlates of missingness were found using the **VIM** package for R (Kowarik & Templ, 2016), as described in the next chapter.

MAR maximum likelihood accounts for missingness in a dependent variable, but missingness on covariates may also be accommodated by bringing covariates into the model, thus invoking FIML (Muthén et al., 2017). The advantage of using FIML (versus pairwise or listwise deletion) is that all cases are used in the analysis. The disadvantage is that distributional assumptions are made about the covariates, a restriction normally only placed on the dependent variables. However, these concerns are minimized when the amount of missingness is low, as in the current study (Muthén et al., 2017).

Mediation and Moderation

The complexity of the statistical model implemented in this study stems from the simultaneous inclusion of both mediated and moderated effects. This statistical complexity is necessary to capture the inherent sophistication of the phenomenon under study, and specifically whether this phenomenon functions similarly for both Title IV-E stipend recipients and non-recipients. Within each group, job satisfaction mediates the associations between distal predictors and turnover intent. However, it is possible the presence or magnitude of any individual indirect effect is different across the groups. This represents a case of moderated mediation (MacKinnon et al., 2007), where the presence or strength of the mediated effects depends on the level of the moderator (in this case, the Title IV-E grouping variable). Testing for moderated mediation helps answer whether the mechanism through which predictors influence outcomes is different across groups.

In terms of moderated mediation, the investigator is interested in both the simple indirect effects (i.e., the indirect effects estimated within each group) and the differences in indirect effects across groups (Ryu & Jeewon, 2017). The differences in indirect effects could be different because of differences in path *a* (i.e., between the predictor and mediator), the path *b*

(i.e., between the mediator and outcome), and/or the product of the two $a \cdot b$. Performing bootstrapping in a multiple-group path analysis framework permits testing differences in a , b , and $a \cdot b$ across groups (Ryu & Jeewon, 2017).

As a final note, all continuous variables were group mean centered (i.e., mean deviation scores) to minimize problems with collinearity associated with interaction terms (Aiken & West, 1991). For example, consider the example of focal variable X , moderator Z , and the interaction term XZ . XZ will often be highly correlated with both X and Z , potentially causing problems with the estimation of model parameters. Centering variables reduces this collinearity.

Summary

This chapter provided a basic overview of the methods and statistical techniques employed in the current study. Means of measuring several constructs were presented, including ITS, job satisfaction, work-related self-efficacy, social integration, role overload, salary satisfaction, and professional development. It was explained these constructs are all measured using single items, which are listed in Appendix B. The discussion also included an overview of the model building strategy, which comprises a series of preliminary models and competing versions of the final model, which will be pared to the simplest statistically defensible model that adequately describes relations among the constructs. Information was also included pertaining to technical aspects of the analysis, such as statistical estimation methods and missing data handling. The chapter closed with a discussion of analyzing mediation and moderation together in the context of multiple-group path analysis.

Chapter 4: Results

This chapter presents all results of the main statistical analysis of this study, along with several ancillary and preliminary analyses. These results include the following: (a) missing data analysis; (b) data screening; (c) establishing discriminant validity; (d) descriptive statistics; (e) preliminary models; (f) process of constructing the final model; (g) final model results; (h) model diagnostics; (i) post-hoc power analysis. Tables 1 through 10 support the discussion in this chapter.

Missing Data Analysis

In the non-Title IV-E group ($n = 716$), approximately 4% of the overall data are missing and the minimum covariance coverage is approximately 84%; for the Title IV-E group ($n = 253$), approximately 2% of data are missing and the minimum covariance coverage is approximately 90%. Sample size requirements to achieve sufficient statistical power and accuracy vary according to several factors, including number of model parameters to be estimated, missing data, distribution of variables, and strength of associations among the variables (Muthén & Muthén, 2002). The adequacy of the present study's sample size is discussed in detail at the end of this chapter.

Maximum likelihood estimation requires the missing data mechanism to be missing at random (MAR). Data are MAR when “there is no relationship between the propensity for missing data on Y [i.e., a dependent variable] and the values of Y after partialling out other variables” (Enders, 2010, p. 6). Although it is not possible to definitively conclude the missing data mechanism is MAR within any particular analysis, the tenability of this presumption is increased if the model includes variables that are correlated with missingness or correlated with another variable that has missing data (Enders, 2010). Accordingly, the investigator performed a

missing data analysis using the **VIM** package for R (Templ & Filzmoser, 2008). This package permits the researcher to visually identify variables that are correlates of missingness on other variables. For instance, Figure 3 reveals how scores on item 22.4 (intent to retire from the agency) are related to missingness for item 22.3 (job satisfaction). In this case, it can be seen the boxplot showing the distribution of scores on ITS (item 22.4) when job satisfaction (22.3) is missing are substantially lower than for cases where job satisfaction information was present. The final model contained several variables that were correlates of missingness, thus supporting the presumption of MAR.

Data Screening

A preliminary data screening was conducted to check for out of range values, outliers, and potential violations of assumptions associated with multivariate statistical analysis (Tabachnick & Fidell, 2013). Table 2 shows, for each group, minimum/maximum values, means, and standard deviations are plausible for all continuous variables. Table 2 also indicates the measures of age, employment duration, and years of prior experience are positively skewed, which is graphically depicted in the box-and-whisker plots in Figure 4. This skew (along with kurtosis, especially for years prior social service employment and years prior non-social service employment) represent potential departures from normality. Likewise, all Likert items exhibit varying degrees of excess skew and/or kurtosis. As discussed in Chapter 3, these departures from normality will be accommodated using robust maximum likelihood estimation and bootstrapping.

Table 4 presents variance inflation factor (VIF) for variables to be used as predictors in the final model. VIF provides a measure of multicollinearity among explanatory variables in regression models (Fox, 1991). Multicollinearity is caused by high inter-item correlations or

multiple correlations, and it results in less precise parameter estimates (i.e., higher standard errors). VIFs are generally low for all variables in both groups except items 25.1 and 25.2, respect from supervisor and support from supervisor, respectively. Furthermore, examination of Tables 3a and 3b reveal bivariate correlations between these variables are quite high in both groups ($\approx .9$), which is the cutoff suggested by Tabachnick and Fidell (2013). It appears these items are not tapping into distinct aspects of supervisor relations. Accordingly, these two items were parceled (i.e., averaged) in subsequent modeling steps. Parceling is appropriate when items are indicators of the same underlying construct and parcels often have better psychometric properties (i.e., higher reliability) than their constituent items (Little, 2013).

Although VIF does not indicate a problem with the two items measuring role overload (26.2 and 26.3), inspection of Tables 3a and 3b reveal high bivariate correlations ($\approx .7$). In light of these high zero-order correlations, the complexity of the final model, and the fact that the different wording in these items is not of substantive interest, items 26.2 and 26.3 were also parceled. Aside from the aforementioned items, examination of bivariate correlations and VIFs indicates no problems with collinearity.

Discriminant Validity

Kenny (1979) cautioned researchers to check for evidence of discriminant validity instead of assuming items intended to represent separate constructs actually do represent different constructs rather than tapping into an overarching, general construct. In other words, while individual survey items might be intended to represent distinct concepts, in actuality they might be tapping into slightly different aspects of a single, overarching construct. He stated this is especially important when the measures are obtained using a single method (e.g., self-report questionnaires). If researchers proceed with causal modeling prior to ensuring discriminant

validity, it is possible to misattribute causal relations among variables when, in fact, they are all caused by a single, underlying factor.

To preclude this possibility, the investigator fit a single factor CFA model to the Likert items. Global model fit indices revealed poor fit for both the non-IVE group: $\chi^2(77) = 744.09$, $p < .001$; RMSEA = .110, 90% CI [.103, .117]; CFI = .647, TLI = .583, SRMR = .092 and the IVE group: $\chi^2(77) = 289.76$, $p < .001$; RMSEA = .105, 90% CI [.092, .117]; CFI = .634, TLI = .567, SRMR = .092. By comparison, a good fitting model would be indicated by a non-significant chi-square test, RMSEA $\leq .06$, CFI/TLI $\geq .95$, and SRMR $\leq .09$ (Hu & Bentler, 1999). That the data are not well represented by a single common factor provides evidence the scale items are tapping into separate constructs, thus supporting discriminant validity. Stated another way, it is reasonable to assume the Likert items are not measuring a single construct but instead represent different constructs, and it is therefore appropriate to use path analysis to model relations among these constructs (Kline, 2016).

Measurement of Intent to Stay

Three different measures of ITS were assessed on the survey: items 22.4, 22.5, and 22.6. As previously discussed, findings in Strand et al. (2010) and Collins-Camargo et al. (2012) were confounded because the instruments measuring turnover intent did not differentiate between workers who wanted to leave because of reasons related to undesirable turnover and those who wanted to leave because they were approaching retirement. This is probably the reason items 22.5 and 22.6 are more highly correlated with each other than item 22.4, as shown in Tables 3a and 3b, which depict bivariate correlations for the non-Title IV-E and Title IV-E groups, respectively. As discussed in the literature review, item 22.3, job satisfaction, is expected to correlate positively with intent to stay. For the non-Title IV-E group, the correlation between the

single item intent to stay measure (22.4) and job satisfaction is slightly stronger than job satisfaction's correlation with the factor score for a composite of all three items (i.e., a latent variable indicated by the three ITS items): .48 versus .43, $t_{\text{Difference}} = 2.26$, two-tailed $p = .024$. The difference is even greater for the IV-E group, where the respective correlations are .51 and .39 ($t_{\text{Difference}} = 3.12$, two-tailed $p = .002$). These findings further reinforce the decision to use item 22.4 as a sole indicator of ITS: not only is this item conceptually closer to the desired construct (i.e., it is able to differentiate undesirable turnover from turnover related to retirement), but also it is more strongly correlated with job satisfaction, a key variable in the model, serving as both a mediator and the proximate assumed cause of ITS. Thus, all subsequent modeling steps were conducted using item 22.4 as the operationalization of ITS.

Descriptive Statistics

The response rate was approximately 54%, which is comparability to other, similar studies and in line with response rates for organizational studies collecting data from individuals (Baruch & Holtom, 2008). Tables 1 through 3 present univariate and bivariate descriptive statistics for the sample data, presented in two groups (Title IV-E recipients and non-recipients, respectively). The groups are rather similar in terms of location (i.e., rural versus urban), gender, ethnicity, and manager/supervisor status, although the Title IV-E recipient group was slightly younger with less work experience. However, the Title IV-E group has a notably higher proportion of both BSW (51% versus 19%) and MSW (49% versus 7%) respondents.

In terms of responses to Likert items measuring various work-related attitudes, the groups are remarkably similar in both the central tendency (mean) and variability (standard deviation). In both groups the lowest endorsed item was, by far, salary satisfaction, with nearly 30% of respondents recording the lowest possible endorsement (i.e., a score of one on a five-point scale).

The highest endorsed items were self-assessed skills and items pertaining to social integration (i.e., items 25.1 through 25.4), which all had means greater than 4.0. The remaining items ranked somewhere below these items and above salary satisfaction.

Preliminary Models

A set of preliminary models were constructed to check for the presence of interaction effects suggested in the literature review. Each model contained only one interaction term and its component first-order terms, and each model was run separately for each group. Testing interaction effects one at a time ensured maximum statistical power was available, which is an important consideration given that statistical power for tests of interaction terms is typically low (Aiken & West, 1991). Table 5 summarizes findings from the preliminary models.

For the sake of completeness, interaction terms with p -values approaching significance ($p < .15$) were included the full model depicted in Figure 2 to determine if significance could be achieved when controlling for other factors. In Table 5, there are five results that approached significance using the $p < .15$ criterion and one that achieved significance using a criterion of $p < .05$. However, Table 5 contains results from 36 individual tests of significance, with no correction for inflation of Type I error rates. Therefore, it would be expected that as many as one or two significant results would be obtained by chance alone, using a criterion of $p < .05$ ($36 * .05 = 1.8$). Performing a multiple degree of freedom test in the full model, however, does control Type I error rate.

Within non-Title IV-E stipend respondents, none of the interaction effects (i.e., age*rural, employment duration*coworker respect, employment duration*position, employment duration*supervisor relations parcel, rural*MSW) tested with intent to stay (ITS) as a dependent variable achieved significance. In addition, a corresponding multiple degree of freedom Wald

test also failed to achieve significance, $\chi^2 (df=5) = 5.09, p = .40$; this indicates simultaneously constraining all interaction effects to zero does not materially worsen model fit. However, the one interaction effect with job satisfaction as the dependent variable (i.e., rural*BSW) did achieve significance ($p = .04$), so it will be retained in the next modeling step. Within Title IV-E respondents, the pattern of results were similar with one exception. The interaction effect of age*rural achieved significance for ITS ($p = .02$). That this interaction was significant for Title IV-E stipend recipients but not for non-recipients indicates Title IV-E may moderate the strength of this effect. As such, the age*rural interaction effect will be retained in the subsequent modeling step to formally check if Title IV-E moderates this association.

Another set of preliminary models were constructed to make simultaneous checks of the various aspects of work-related self-efficacy. To reduce the number of parameters estimated in the latter modeling stages, it is desirable to eliminate measures of work self-efficacy that do not relate to either job satisfaction or ITS. Again, the most direct way of testing this is using a multiple degree of freedom Wald test. The patterns of significance of the work-related self-efficacy variables are different in each group. One similarity, however, is items 32 and 34, pertaining to administrative skills and skills working with culturally diverse populations, respectively, failed to achieve significance in either group for either dependent variable (i.e., job satisfaction and ITS). In addition, multi-degree of freedom Wald tests for each group indicated simultaneously constraining all four coefficients to zero did not materially worsen model fit: Title IV-E group, $\chi^2 (df = 4) = 1.15, p = .89$; non-Title IV-E group, $\chi^2 (df = 4) = 4.34, p = .36$. Accordingly, items 32 and 34 will not be included in future modeling steps.

Constructing the Final Model

Having completed several preliminary modeling steps, the discussion now turns to constructing the final model. The approach outlined in Muthén et al. (2017) was followed, which consists of a model building approach in a series of steps. Since there are several steps involved, results of this process are summarized in Table 6.

In the first model (M1), the model shown in Figure 2 was estimated using *Mplus*, but with the stipulation that all regression slopes be constrained to equality across groups. A second model, designated M1.1, was then estimated, which was the same as M1 except with residual variances also constrained to equality across groups. M1 and M1.1 were then compared using a likelihood ratio test (properly rescaled since robust maximum likelihood estimation was used). This modeling step was necessary to determine if residual variances for the two dependent variables (job satisfaction and ITS) are the same in both groups (i.e., Title IV-E stipend recipients and non-recipients). Stated differently, this step involves checking to see if the proportion of explained variance, or R^2 , is the same in both groups. This test did not achieve significance, $\chi^2 (df=2) = 0.28, p = .87$, indicating the fit of M1.1, with residual variance constrained to equality, was not significantly worse than model fit of M1, wherein residual variances were freely estimated in each group. Therefore, the model shown in Figure 2 explains about the same amount of variance in both job satisfaction and ITS, respectively, across both groups. Accordingly, in subsequent modeling steps, residual variance will be constrained to equality; this will enhance model parsimony and statistical power.

The *Mplus* output from M1.1 contained modification indices, which show parameters that, if added to a model or freely estimated rather than constrained, would improve model fit by a statistically significant margin. In a multi-group context, regression parameters with a

significant modification index suggest that freeing these particular parameters could significantly improve model fit, thus indicating the grouping variable could moderate the strength of these regression slopes (Muthén et al., 2017). In addition to using modification indices, single degree of freedom Wald tests can also be used to check for parameters that significantly differ across groups. In very large samples, the Wald test and modification indices should yield similar results, but they sometimes can differ when sample size is finite or under conditions of non-normality (Pawitan, 2000). Thus, Muthén et al. (2017) recommended using both approaches when screening models for moderation by the grouping variable. To generate the Wald tests, M1.2 was estimated, which was identical to M1.1 except all regression slopes were freely estimated across both groups. The Wald tests consisted of comparing each regression slope across groups to determine if the differences were significant. Table 7 shows results of the modification indices and Wald tests. In the present study, these two approaches were in agreement in most cases, with only six instances where one method revealed the slopes could vary significantly across groups and the other method did not.

The next step consisted of following up the exploratory results of the Wald tests and modification indices with multiple degree of freedom tests; that is, testing groups of regression slopes together rather than individually. Multiple degree of freedom tests are superior to single degree of freedom tests in that they have more statistical power (Schumacker & Lomax, 2010) and they take into account correlation among various parameter estimates (Muthén et al., 2017). First, a model (M1.2.1) was constructed in which the slopes that the modification indices and Wald tests indicated were homogenous were constrained to equality across groups, then the fit of this model was compared to an unrestricted model previously discussed (M1.2), wherein regression parameters were freely estimated for each group. A scaled likelihood ratio test

comparing these models did not achieve significance, $\chi^2 (df=34) = 31.50, p = .59$, indicating model fit did not significantly worsen. This provides additional evidence this group of regression slopes does not differ for Title IV-E stipend recipients and non-recipients.

M1.2.1 was then compared with M1.1, the model in which all regression slopes are held constant across both groups; this procedure allows for a multiple degree of freedom test for the regression slopes indicated by Wald tests or modification indices (as shown in Table 7) to possibly differ across groups. This test did achieve significance, $\chi^2 (df=7) = 32.45, p < .001$, indicating worse model fit if the seven parameters identified in Table 7 are constrained to equality across groups. This, in turn, provides further evidence group membership (i.e., receipt of Title IV-E stipends) moderates the relations among variables for the regression parameters indicated in Table 8. Thus, M1.2.1 was retained as the final model. Based on the criteria discussed earlier (Hu & Bentler, 1999), model fit of M1.2.1 was excellent: $\chi^2(40) = 35.32, p < .68$; RMSEA = .000, 90% CI [.000, .026]; CFI = 1.000, TLI = 1.000, SRMR = .008.

A Note about Standardized Estimates and Effect Sizes

The American Psychological Association has noted the importance of reporting effect sizes when variable scaling is not intuitively meaningful (e.g., Likert scales) (Wilkinson, 1999). One commonly used effect size in a regression context is the standardized regression coefficient, which is scaled to standard deviation units (Kelley & Preacher, 2012). Nevertheless, in multiple group analysis, standardized regression coefficients can vary across groups even when the unstandardized coefficients are equal. This misleading result occurs not because the effect sizes (i.e., strength of relations) are different across groups, but simply owing to differences in standard deviation across groups (Muthén et al., 2017). This phenomenon can also affect estimates of the coefficient of determination (R^2), since it relies on standardized estimates of

residual variance. Since this study features the use of a multiple group analysis, standardized regression coefficients are not reported. One mitigating factor, however, is that although the Likert items do not have an inherently meaningful metric, they are all on the same five-point scale, so the unstandardized coefficients may be used to indicate the relative importance or strength of regression coefficients. Measures of R^2 are reported in this chapter, but subject to the limitations noted above in this paragraph.

Final Model Results

Tables 8 and 9 present relevant results from the final model (M1.2.1). The left-hand column lists model parameters, and the remaining columns list parameter estimates (and their standard errors), 95% confidence intervals of the estimates, and the corresponding z -statistics and p -values for the non-Title IV-E group, the Title IV-E group, and the differences between the two. Note that the estimates for group differences are not reported for those parameters that were discovered not be significantly different across groups during the model building steps described in the previous section. Furthermore, although some estimates for group differences contain results that are non-significant, all group differences reported (i.e., all that are not annotated as “n.s.,” or non-significant) did achieve statistical significance when subjected to multiple degree of freedom testing. As described in the previous section, multiple degree of freedom tests have more statistical power than single degree of freedom tests, which is why some of the single degree of freedom tests in the group differences column do not achieve $p < .05$. The z -statistics are computed by dividing parameter estimates by their corresponding standard errors; z -statistics with an absolute value greater than 1.96 correspond to $p < .05$. Confidence intervals are symmetrical and based on normal theory, wherein the 95% confidence limits are calculated as plus/minus 1.96 standard error units. For all relevant parameter estimates (including direct

effects, indirect effects, and tests for differences across groups) empirical (bootstrap) confidence intervals were found to be nearly identical to the standard, normal theory intervals, so they are not reported. This means the tests of indirect effects are based on the traditional Sobel test (Sobel, 1982).

Because all continuous variables (including x , or predictor, and y , or outcome, variables) were group mean-centered prior to entry into the final model, the model intercepts can be interpreted meaningfully. In regression models, intercepts represent the predicted score on the x variable when all y variables take a value of zero. Since the continuous variables were group mean-centered, a score of zero on a y variable indicates a score equal to the group mean for that variable. Similarly, a score of zero on an x variable indicates a score equal to the group mean for that particular outcome. Thus, the intercepts can be interpreted as the predicted group mean deviation score on the outcome variable for a person scoring at the group mean value for all continuous predictors and zero for all binary predictors (i.e., non-manager, urban, female, and White).

Values for proportion of variance explained (i.e., R^2) in job satisfaction and ITS are listed in Table 8. Within the non-Title IV-E group, the model explained approximately 42% of the variance in ITS and 46% of the variance in job satisfaction; the corresponding values for the Title IV-E group were 47% and 41%, respectively. As reported in the previous section, however, the differences between the groups were non-significant, indicating the model's predictive power was roughly the same for both groups.

To evaluate the influence of each explanatory variable, it is necessary to examine results in both Table 8 and Table 9. Each regressor can influence ITS directly, indirectly via job satisfaction, or both directly and indirectly. Conversely, all regressors' influence on job

satisfaction is direct, since there are no mediators prior to job satisfaction. Table 8 contains partial regression slopes, which represent the direct influence of regressors on the two outcomes in the model, job satisfaction and ITS, while controlling for the other variables in the model. Table 9, meanwhile, depicts the indirect influence (i.e., mediated through job satisfaction) and total influence (i.e., direct plus indirect influence) of each regressor on ITS.

Influence of job satisfaction.

As shown in Table 8, the partial regression coefficient for the influence of job satisfaction on ITS is 0.34. This parameter estimate is interpreted thusly: when comparing two respondents who are identical on all other variables included in the model except job satisfaction, the respondent with higher satisfaction is predicted to have an ITS score that is, on average, 0.34 points higher (per one-unit difference in job satisfaction, on a five-point scale). Furthermore, this effect did not differ significantly when comparing Title IV-E stipend recipients and non-recipients.

Beyond the intuitive conclusion that increased job satisfaction predicts higher ITS, these findings have several important implications for the remaining explanatory variables in the model. Note that in the lower portion of Table 8, all direct effects leading from the explanatory variables to job satisfaction do not differ across groups. Since the regression paths leading to job satisfaction and, as discussed above, the path leading from job satisfaction to ITS are all homogeneous across groups, there is no way for any indirect effects (i.e., those mediated by job satisfaction) to differ across groups. Therefore, the only paths that can differ across groups are direct effects from explanatory variables to ITS; all mediated effects discussed below are equal in both groups.

Influence of employment duration.

Within the non-Title IV-E group, the partial regression coefficient of employment duration is 0.03. Thus, when comparing two respondents who are identical on all other variables included in the model except employment duration, the respondent with higher longevity is predicted to have an ITS score that is, on average, 0.03 points higher (per year, on a five-point scale). The partial regression slope of employment duration is also 0.03 in the Title IV-E group. Although earlier modeling steps indicated the influence of employment duration is moderated by group membership (as described in the previous section), the regression slopes in each group are identical (at least when rounded to the hundredths). As a follow up test, another model was constructed: the new model was identical to the final model (M1.2.1) except with the regression slopes for employment duration constrained to equality across groups. A likelihood ratio test comparing these models did not achieve significance, $\chi^2 (df=1) = 0.85, p = .36$, indicating the influence of employment duration is not dependent upon Title IV-E status (additionally, other model parameters were not appreciably different in the restricted model; that is, restricting the employment duration slope across groups did not materially affect other parameter estimates). Moreover, as indicated in Table 9, the indirect influence of employment duration on ITS via job satisfaction was non-significant. Finally, the influence of employment duration on job satisfaction did not achieve significance, and group differences for this parameter were also non-significant.

The dataset also included two other measures of work experience: prior social service employment and prior non-social service employment. Prior social service experience did not significantly influence job satisfaction in either group, therefore the indirect effect of prior social service on ITS through job satisfaction was also non-significant. Moreover, the direct influence

of prior social service experience on ITS was non-significant for non-Title IV-E recipients. However, its influence on ITS within the Title IV-E group was significant, and the difference in regression slopes between the two groups also achieved significance. Only among Title IV-E respondents, those with greater prior social service experience tended to express higher ITS. Finally, prior non-social service experience did not achieve significance for ITS or job satisfaction, and the parameter estimates were not different across groups. *In summary, PCW workers with greater employment duration, regardless of Title IV-E status, tend to express higher ITS, and this influence is not mediated by job satisfaction. In addition, workers with greater prior social service experience also express higher ITS, but only among Title IV-E workers, and the effect size is nearly as great as for employment duration.*

Influence of professional training (social work degree).

The direct influence of BSW status on ITS did not quite achieve significance ($p = .07$; however, see discussion in section titled Final Model Diagnostics later in this chapter), and the partial regression slope was not different across groups. The influence of BSW on job satisfaction was also non-significant, but this parameter was involved in a statistically significant interaction term (BSW*rural), meaning the BSW partial regression slope is conditional, or dependent upon the value of another variable in the model. Specifically, it is conditional on the dummy indicator for rural location being equal to zero. Therefore, the influence of BSW on job satisfaction (shown in Table 8 as 0.04) is non-significant when the rural dummy indicator equals zero (i.e., for urban respondents). However, the significant interaction term of BSW*rural indicates the partial regression slope of BSW is significantly different for rural respondents. The influence of BSW status on job satisfaction for rural workers is given by summing the partial regression coefficients for the BSW indicator (0.04) and the interaction term (0.25), which equals

0.29, and is statistically significant ($p < .001$). Therefore, between two rural respondents who differ on BSW status but are equal on other model variables, the BSW degree holder is expected to express 0.29 units higher job satisfaction, on average.

Furthermore, since the conditional effect of BSW status on job satisfaction is significant, and the influence of job satisfaction on ITS is significant, there is also a significant conditional mediated effect of BSW status on ITS via job satisfaction; an estimate of this effect is given by the product of the simple slope of BSW status on job satisfaction when the rural indicator equals one (0.29, as discussed above) and the regression coefficient of ITS on job satisfaction, which is 0.34, as shown in Table 8. Thus, the conditional mediated effect of BSW status on ITS through job satisfaction among rural workers is $0.29 \times 0.34 = 0.10$, which achieved significance ($p = .001$). This conditional effect can be interpreted as follows: for two rural respondents who differ on BSW status but are equal on other model variables, the BSW degree holder is expected to express 0.10 units higher ITS, on average, as a result of the tendency of BSW degree holders to feel greater job satisfaction, which in turn leads to greater ITS. *In summary, BSW holders tend to report greater job satisfaction and ITS, but only among rural respondents, and this effect is the same regardless of Title IV-E stipend status.*

Although MSW status did not influence job satisfaction in either group, possession of an MSW degree was associated with lower ITS for both Title IV-E stipend recipients and non-recipients. However, group membership moderated this association: the effect size was about 40% lower for Title IV-E stipend recipients. This parameter estimate for the non-Title IV-E group is -0.50 and may be interpreted thusly: when comparing two respondents who are identical on all other variables included in the model except MSW status, the holder of an MSW degree is predicted to have an ITS score that is, on average, 0.50 points lower (on a five-point scale) when

compared with a non-MSW respondent. The same interpretation holds in the Title IV-E group, except the penalty to ITS is only 0.29 points. *In sum, possession of an MSW degree had no influence on job satisfaction, but it did have a direct, negative influence on ITS, although the effect is somewhat less among Title IV-E stipend recipients.*

Influence of professional development.

The parameter estimate for ITS regressed on professional development did not achieve significance, and was not significantly different across groups. Conversely, the influence of professional development on job satisfaction was significant, and again homogeneous across groups. Moreover, as shown in Table 9, the indirect effect of professional development on ITS via job satisfaction also achieved significance. The parameter estimate of the indirect effect, 0.11, was the same across both groups and may be interpreted thusly: two respondents with a one-unit difference in professional development satisfaction are expected to differ by 0.11 points on their reported ITS as a result of the tendency for those with higher professional development satisfaction to also have higher job satisfaction, which in turn leads to higher ITS. Since the direct effect of professional development on ITS did not achieve significance, the influence of professional development on ITS is completely mediated by job satisfaction. *In summary, increased satisfaction with professional development leads to higher job satisfaction and therefore higher ITS, and this effect holds regardless of Title IV-E status.*

Influence of social integration.

The study included three measures of social integration, including coworker respect (25.3), work unit cohesiveness (25.4), and two questions about supervisor relations (25.1 and 25.2), which were parceled together as discussed earlier in the chapter. For all three variables, the direct and indirect effects discussed below were homogeneous across groups.

Regarding coworker respect, the direct effects on both ITS and job satisfaction were significant and negative, meaning workers with higher perceived levels of coworker support tended to express lower ITS and job satisfaction. Furthermore, the indirect effect of coworker respect on ITS through job satisfaction achieved significance, as shown in Table 9. Since the direct influence of coworker respect on ITS was significant, job satisfaction only partially mediates the influence of coworker respect. Accordingly, it makes sense to interpret the total effect – the summation of direct and indirect effects – of coworker respect on ITS, shown in Table 9 to be -0.14. This estimate may be interpreted thusly: two respondents with a one-unit difference in perceived coworker respect are expected to differ by 0.14 units in total on ITS, with the respondent reporting higher coworker respect expressing lower ITS.

Perceived work unit cohesiveness did not directly influence ITS, but it did influence job satisfaction, meaning that it also indirectly influenced ITS via job satisfaction, as shown in Table 9. Perceptions of higher levels of work unit cohesiveness tended to increase ITS, and this relation was completely mediated through job satisfaction. A similar pattern is seen with the supervisor relations parcel: perceptions of good supervisor relations increased job satisfaction and subsequently ITS, and this association was completely mediated by job satisfaction since the direct effect of supervisor relations on ITS was non-significant.

In summary, the influence of social integration on ITS was mixed. Higher levels of perceived coworker respect tended to be associated with lower ITS, with the effect partially mediated through job satisfaction. In contrast, work unit cohesiveness and supervisor relations positively related to ITS, and the effect was completely mediated through job satisfaction. These effects were constant across both groups.

Influence of role overload.

The parcel of role overload items (26.1 and 26.2) positively influenced ITS, and this relation was completely mediated by job satisfaction since the direct influence of role overload on ITS was non-significant. As a reminder, higher scores on the role overload parcel correspond to lower perceived role overload. Based on the estimate of the indirect effect presented in Table 9, two respondents with a one-unit difference in perceived role overload are expected to differ by 0.09 units on their reported ITS as a result of the tendency of those under lower workload stress to feel greater job satisfaction, which in turn leads to higher ITS, and this pattern is consistent across groups. *In summary, for both Title IV-E recipients and non-recipients, lower perceived role overload serves to increase ITS via job satisfaction.*

Influence of work-related self-efficacy.

The model included three measures of work-related self-efficacy, including perceived degree to which university education was effective in preparing respondents for roles in PCW (27.1), as well as self-assessed casework skills (28) and skills working with disabled/special needs clients (36). In both groups, increased perceptions of preparedness from university education was directly related with higher ITS, and this relation was not mediated through job satisfaction, since the influence of university preparedness did not influence job satisfaction. Self-assessed casework skills influenced directly influenced ITS, but only for Title IV-E recipients. In addition, the difference in regression slope parameter estimates across groups was significant, indicating Title IV-E status moderates the influence of self-assessed casework skills on ITS. Also, the influence of casework skills on ITS was strictly direct, since casework skills did not significantly influence job satisfaction. Finally, the influence of self-assessed disabled/special needs client skills was also different across groups. Among non-Title IV-E

recipients, the influence of disabled/special needs skills on ITS was completely mediated by job satisfaction, whereas for Title IV-E respondents the direct influence on ITS was also significant. In both groups, increased confidence in one's disabled/special needs skills led to increased job satisfaction and ITS. *To summarize, the influence of work-related self-efficacy on ITS was generally different for Title IV-E recipients and non-recipients, but only in terms of self-assessed casework skills and skills working with disabled/special needs clients. The influence of university-gained skills on ITS was the same for both groups. Overall, self-assessed job skills appear to be more relevant for turnover intentions among Title IV-E recipients.*

Influence of compensation.

Increased satisfaction with salary predicted higher ITS, both directly and indirectly via job satisfaction. Because both the indirect and direct effects were significant, it makes sense to interpret the total effect (combined direct and indirect). As shown in Table 9, the parameter estimate for the total influence of salary satisfaction on ITS is 0.12; thus, two respondents with a one-unit difference in salary satisfaction are expected to differ, on average, by 0.12 units in total on ITS, after controlling for other variables in the model. Furthermore, this pattern was the same regardless of Title IV-E stipend status. *In summary, higher salary satisfaction tended to increase ITS, both directly and indirectly via job satisfaction, and Title IV-E status did not moderate this association.*

Influence of position/job type.

After controlling for other explanatory variables in the model, supervisors' and managers' expressions of both job satisfaction and ITS were statistically indistinguishable from front-line respondents, and this pattern was the same regardless of Title IV-E stipend status.

Influence of demographic characteristics.

Within the non-Title IV-E group, the partial regression slope estimate for ITS regressed on a dummy variable indicating rural location status is 0.22 and is statistically significant, as shown in Table 8. Accordingly, when comparing two respondents who are identical on all other variables included in the model except location, the rural respondent is predicted to have an ITS score that is, on average, 0.22 points higher (on a five-point scale) when compared with an urban respondent. However, the rural indicator was not significant for the Title IV-E group. To summarize, *non-Title IV-E rural workers express higher ITS than urban counterparts, but this pattern is not seen among Title IV-E recipients.*

The partial regression slope estimate for ITS regressed on age is 0.03 and is statistically significant. This parameter estimate is interpreted thusly: when comparing two respondents who are identical on all other variables included in the model except age, the older respondent is predicted to have an ITS score that is, on average, 0.03 points higher (on a five-point scale) for each year of age difference. The interaction term involving age and rural status did not achieve significance, indicating the influence of age on ITS is the same for rural and urban workers. Title IV-E status did not affect the strength of the relation between age and ITS, because the partial regression slope was not different for the two groups. Thus, older respondents tended to express higher ITS relative to their younger colleagues, controlling for other factors, and this pattern was consistent across both groups. However, the influence of age on job satisfaction was not significant in either group, therefore the indirect effect of age on ITS through job satisfaction was non-significant, as indicated in Table 9. Therefore, *the influence of age on ITS is significant, but it is only direct, and not mediated by job satisfaction; this pattern is consistent across both groups.*

Results in Table 8 show non-White respondents tend to express lower ITS and job satisfaction compared with their White colleagues, and this pattern is consistent across groups. However, whether the influence of race/ethnicity status is transmitted to ITS through job satisfaction is debatable, since the indirect effect failed to achieve significance ($p = .06$). *Nevertheless, the influence of race/ethnicity seems clear: regardless of Title IV-E status, job satisfaction and ITS were lower for non-White PCW workers.*

The influence of gender is somewhat difficult to interpret given the pattern of findings shown in Table 8. Although a dummy indicator for gender failed to achieve significance in either group, the difference in partial regression slopes for the two groups achieved significance. Stated differently, even though the slopes achieved significance in neither group, the difference between the two slopes was significantly different than zero. However, the partial regression coefficient for the Title IV-E group nearly achieved significance ($p = .06$), revealing males expressed slightly lower (0.32 points on average) ITS than females, within the Title IV-E group. In terms of job satisfaction, the influence of gender was non-significant, with no statistically significant difference across groups. Accordingly, the indirect effect of gender on ITS through job satisfaction was also non-significant, as shown in Table 9. *In summary, while the direct influence of gender on ITS was non-significant within each group, the difference between groups was significant, and it appears male PCW workers who received Title IV-E stipends might have lower ITS relative to female colleagues who received the stipend.*

Final Model Diagnostics

Mplus has the capability of computing several diagnostic statistics to help assess the quality of the model estimates. In a multiple group model, the statistics are computed separately for each group. The diagnostic statistics computed for the final model included the loglikelihood

distance influence measure (Cook & Weisberg, 1982), Cook's D (Cook, 1977), and Mahalanobis distance (Rousseeuw & Van Zomeren, 1990). Influence statistics such as the loglikelihood influence and Cook's D describe the magnitude of change in regression coefficients when a particular case is excluded from the analysis, while Mahalanobis distance is used to identify potential multivariate outliers. Recommended cutoff values for identifying potentially unusual cases were 1.00 for the loglikelihood influence measure and Cook's distance, while a p -value less than .001 was used for Mahalanobis distances (Tabachnick & Fidell, 2013).

The non-Title IV-E group, with its larger sample size, had relatively few influential cases. Only 77 cases out of 716 exceeded the cutoff criteria discussed above, with most of these just barely surpassing the limits. The maximum Cook's distance was 1.106 while the maximum loglikelihood influence statistic was 6.996, although the vast majority exceeded 1.00 by a small amount. For the Title IV-E group, all but one case had a Cook's distance greater than 1.00, and many also had loglikelihood influence statistics greater than 1.00. However, only four cases had a Mahalanobis p -value less than .001. Notably, three cases had Cook's distances much higher than the others (i.e., greater than 200). A sensitivity analysis was performed, recomputing the final model with these three cases omitted. Model estimates did not change appreciably, and only one parameter estimate changed in terms of statistical significance. Namely, in the final model presented in Table 8 (with all cases included), the direct influence of a binary BSW indicator on ITS was just non-significant, with a partial regression coefficient of 0.12 and a p -value of .07. With the three most influential cases in the Title IV-E group removed, the regression coefficient is slightly larger at 0.14 and the associated p -value is .04. Thus, possession of a BSW degree could have a positive and direct influence on ITS, although the effect size is quite small. Taken together, outliers appear not to have had a material influence on model results.

Post-Hoc Power Analysis

Statistical power refers to the likelihood a statistical test will yield significant results in the presence of a true population effect (Cohen, 1992). Although several rules of thumb have been offered for minimum sample sizes in the context of SEM, these are often difficult to apply because each model is different (Kline, 2016). Sample size requirements vary according to several factors, including number of model parameters to be estimated, missing data, distribution of variables, and strength of associations among the variables (Muthén & Muthén, 2002). Therefore, reliance on rules of thumb may significantly over- or under-state sample size requirements in the context of a particular study (Wolf, Harrington, Clark, & Miller, 2013). As an alternative, Monte Carlo (MC) simulations offer a more contemporary alternative (Kline, 2016). MC simulations provide an opportunity not only to estimate statistical power, but also to assess the accuracy of parameter estimates and standard errors (Muthén et al., 2017).

An MC simulation works by specifying population parameters (e.g., regression coefficients, means, variances) and generating multiple samples (replications) based on these parameters, then testing a model on each replication, and finally compiling the results (Muthén et al., 2017). An element of randomness is introduced in this process using a pseudo-random number generator (Harrison, 2010). MC simulations are an integral feature of the *Mplus* structural equation modeling application, which the investigator used to perform a post-hoc power analysis. However, MC simulations generally provide only an approximation of statistical power and the quality of parameter estimates, as real data are influenced by departures from normality and missingness, which are not possible to totally replicate in a simulation (Muthén et al., 2017). In fact, the simulations conducted in the present study made several simplifying assumptions, all of which would serve to increase estimated power: normally distributed

variables (except for binary indicators), no missing data, no interaction effects (other than by the grouping variable). Also, note that many regression parameters were held constant across both groups, in line with results from the final model. However, it is possible that some of these parameters would have been determined to vary significantly across groups had statistical power been higher.

Tables 10a and 10b present results of the power analysis; Table 10a contains power information for the final model regression parameters, while Table 10b presents power information for group differences and indirect effects. The guidelines and interpretations that follow were adopted from Muthén and Muthén (2002). The first column, population parameter, is the assumed effect size in the population, and was derived from the final model results. The population parameter is the reference point to which subsequent estimates derived from the MC simulated datasets (in this case, 1,000 datasets were generated) are compared. The next column, average parameter estimate, is the average of parameter estimates over the 1,000 replications. The third column, parameter bias, is obtained using the following equation:

$$Parameter\ Bias = \frac{Avg.Parameter\ Est. - Pop.Parameter}{Pop.Parameter} \quad EQ\ 4$$

This amounts to the percent difference between the specified population parameter and the average parameter estimate. Only four parameters bias estimates (shown in bold font) exceeded the recommended cutoff of 10%: the partial regression slope for the rural indicator within the Title IV-E group, the residual variances for the two dependent variables, and the indirect influence of years of prior social service employment on ITS through job satisfaction. This indicates these three estimates may not be trustworthy. However, the effect sizes for the Title IV-E group rural indicator and the indirect effect of prior social service employment were non-significant and near zero, so parameter bias is not particularly a concern. Standard error bias is

calculated similarly, using the columns standard deviation and average standard error. Standard errors tend to be biased within the Title IV-E group, owing to the restricted sample size in that group. Although not as extensive, several standard errors associated with group differences also exceeded 10% bias, although they were generally close to the cutoff.

The next column, coverage, refers to the proportion of replications in which the 95% confidence interval for the relevant parameter estimate included, or ‘covered,’ the population parameter. All but two of the coverage values for the Title IV-E group were below the recommended cutoff of 0.91, but they were very close. Overall, coverage was acceptable. Finally, the % significant column indicates the proportion of replications in which the relevant parameter estimate achieved statistical significance; for non-zero effects, this is interpreted as statistical power. In general, power estimates of 0.80 or higher are desirable. As an example of how to interpret the power estimate, consider the regression parameter for position (manager or supervisor). The power estimate is 0.256, which indicates – given the specified model and effect size – a significant result for this parameter estimate would be achieved in only about 25% of randomly drawn samples. As indicated in Table 8, this parameter did not achieve significance in the current study. What is not known for certain is why this estimate did not achieve significance; it could be the actual effect in the population is zero, or it could be the power of the test was too low to detect a true effect. What is known, from the power estimate, is that if the true effect size is 0.068, then it would have been unlikely to find this result to be significant given the current model and sample size.

For most of the parameters estimated in the current study, power was unlikely to have met the 0.8 threshold. Several factors bear upon this result and have implications for planning future research, as discussed in greater detail in the following chapter. However, the factor of

sample size will be discussed in more detail here, with the benefit of additional MC simulations. Once initially programmed, MC simulations are easily modified to examine the influence of different sample sizes and, in the case of multiple group analysis, group sizes (Muthén et al., 2017). The investigator performed several simulations, with sample sizes of $n = 700$, $n = 1,000$, and $n = 1,500$, in each case with the whole sample evenly distributed between Title IV-E and non-Title IV-E groups. Balancing the groups had the effect of decreasing bias in the standard errors of group differences, but estimated power for several regression parameters remained low, even as total sample size was increased to 1,500.

However, power is influenced not only by sample size, but also effect size; effect size, in turn, is not only a function of the magnitude of relations among constructs in the true population, but also reliability, or the fidelity of the measuring instrument (Cohen, 1988). Some of the regression parameters for which power is stubbornly low, even at a sample size of 1,500, are also characterized by very low effect sizes. For example, the item relating to satisfaction with professional development opportunities (22.2) has a partial regression coefficient of 0.013 (on a five-point Likert scale) and an estimated power (in a sample of 1,500, split evenly between groups) of 0.081. The low effect size is a consequence of either the related construct not being particularly pertinent to ITS in the true population, or measurement error, or both.

Another factor influencing power is model complexity, or the number of parameters (Wolf et al., 2013). For the sake of comprehensiveness, especially given the lack of clarity in prior literature surrounding the importance of various factors in terms of ITS, many potential explanatory variables were included in the present study. Reducing the number of explanatory variables would, in turn, reduce the number of parameters to estimate, thereby increasing available power for the remaining parameters. While all of these issues are explored more fully

in the next chapter, not only in context of the current study, but also in terms of implications for future research, for now it may be concluded the results of the MC simulations and the insights they reveal about the results obtained in this study must be interpreted in light of not only sample size, but also measurement and model complexity.

Summary

This chapter presented results from ancillary, preliminary, and final model testing, as well as diagnostic results. The chapter opened with a discussion of the missing data analysis, basic screening for multivariate assumptions and collinearity, and a presentation of descriptive statistics. Next, the discussion turned toward results from preliminary modeling steps, followed by a comparison of a series of nested models tested against each other to build the final model. Next, a statistical interpretation of all key parameter estimates from the final model was presented. Finally, the chapter closed with a discussion of model diagnostics and a Monte Carlo simulation for post hoc power analysis. While this chapter presented a technical interpretation of final model results, the next chapter offers substantive interpretations.

Chapter 5: Discussion

This chapter contains implications for PCW agency administrators and managers (practice implications) as well as policymakers. Recall the specific aims of this study outlined in Chapter 1 were to (a) test a causal model of turnover intentions, whereby distal explanatory variables indirectly influence ITS through job satisfaction and (b) identify group differences in the pattern of association within the causal model based on receipt of Title IV-E stipends. The working hypothesis was that individual worker characteristics and perceptions would influence job satisfaction and turnover intentions to a lesser degree among Title IV-E recipients. In this way, Title IV-E would serve as a protective factor against deleterious working conditions that are difficult for managers and supervisors to directly influence, such as workload and pay. From a policy perspective, this finding would, in turn, suggest Title IV-E provides some return on investment. Overall, the findings were mixed in this regard. While Title IV-E stipend receipt appears to mitigate the tendency of urban and MSW-holding workers to express lower ITS, it did not provide a protective factor against dissatisfaction with professional development, workplace relationships, workload, or salary.

Perhaps most important, however, are implications for future research. While the present study offers some insights into potential differences and similarities between Title IV-E recipients and non-recipients, practical and policy implications must be interpreted in light of some important limitations. These limitations are addressed in detail, including how they can be overcome in future research. In the investigator's view, the most important contribution this study makes is in serving as a template for future investigations, building on the multiple-group SEM framework. This chapter includes several conceptual and statistical extensions of the current study that would go a long way toward more fully answering the questions posed in

Chapter 1, to wit, *does Title IV-E have a positive effect on PCW retention and, if so, how is this achieved?*

Implications for Practice

Findings from the current study have several implications for child welfare practice, which, in this context, refer to PCW administrators and managers and the influence they have over agency policies, including selection criteria and organizational interventions (macro level policy implications are discussed in the next section). As Jayaratne and Chess (1984) pointed out, one-size-fits-all interventions are not likely to succeed across child welfare jurisdictions since various workplace factors may have disparate effects on different groups of employees. Indeed, as outlined in Chapter 1, this was one of the two main goals of the current study: identify retention factors that are particularly important to Title IV-E stipend recipients.

Several pieces of evidence emerged from this study indicating the possibility of several important differences between Title IV-E recipient PCW workers and their non-recipient counterparts. As described in Ch. 4, *Constructing the Final Model*, constraining all regression coefficients to equality across both groups significantly worsened model fit compared to a model wherein parameter estimates were freely estimated in each group for the predictors identified in Table 7. This finding reveals the relative importance of some individual characteristics and unique workplace factors are different for Title IV-E recipients and non-recipients. These differences have the potential to inform future management initiatives to boost retention. It is equally important to consider factors that do not vary across groups, and are important factors for retention of all PCW workers. Implications highlighted for managers and administrators focus on measures that are reasonably expected to fall within their scope of influence, rather than presenting ideal solutions that have little chance of implementation (Mor Barak et al., 2006).

Employment duration.

This study offers several important implications for managers and administrators pertaining to employment duration. Not surprisingly, in both groups, longer employment duration was associated with higher intent-to-stay (ITS). Job satisfaction also tended to be higher among those with longer employment duration, although the effect size was lower and did not quite achieve significance. This finding is consistent with Rycraft's (1994) conclusion that workers who remain tend to become more committed as time goes on. If so, then retention efforts might be more effective if they are specifically targeted at less experienced workers. A consistent finding in turnover research (i.e., not limited to PCW) is that most turnover occurs in new hires who often have trouble adjusting to new jobs (Hom et al., 2017). Given that the majority of PCW leave their positions within the first five years of employment, targeted retention efforts to support new PCW workers are warranted.

Moreover, the present study's findings indicate years of prior social service experience (i.e., prior to respondents' current agency) was significantly and positively related to ITS, but only among Title IV-E recipients. It is difficult to know precisely why this might be without further study, but one possibility is that, among Title IV-E recipients, those with prior social service experience are already familiar with PCW work and entered a Title IV-E program with realistic expectations. Conversely, a PCW worker with prior social service experience who did not enter a Title IV-E program might not have the same level of long-term commitment to PCW specifically and may be more open to engaging in social services work outside the PCW field since they did not pursue additional education specific to child welfare. Meanwhile, Title IV-E recipients without prior relevant experience may not have realistic expectations about what actual PCW work entails, and may not ultimately desire to continue working in the PCW field.

This supports Balfour and Neff's (1993) finding that inexperienced caseworkers "may have unrealistic expectations about their jobs, or a limited understanding of the challenges inherent in casework" (p. 483), thus impelling them to leave the field.

This finding is also in line with the attraction-selection-attrition (ASA) cycle described by Schneider (1987). In this framework, "different kinds of organizations attract, select, and retain different kinds of people, and it is the outcome of the ASA cycle that determines why organizations look and feel different from each other" (Schneider, 1987, p. 440). Therefore, certain types of people are attracted to, and retained within, a particular organization or field. Said another way, people who do not fit tend to filter out over time. People who have prior experience in PCW or a related field and who do not fit particularly well are unlikely to further invest in their current career trajectory by enrolling in a Title IV-E stipend program. If this interpretation is correct, then managers would do well to recruit Title IV-E recipients who already have prior social service experience, as these hires might be inclined to remain in PCW longer.

Professional training (social work degree).

There is an ongoing, spirited debate about whether those with a social work degree are superior PCW workers compared with PCW who do not have formal social work training (e.g., Perry, 2016; Rubin & Parrish, 2012; Zlotnik, 2006). Nevertheless, given unwanted turnover is an undeniable problem in PCW, and given it is reasonable to assume obtaining a social work degree is one – but not necessarily the only or best – method of preparing for a PCW career due to the large scope of influence that child welfare has historically held in the field of social work, it follows that PCW managers and administrators would be interested in retaining social work degree holders.

It is from this perspective the present study's findings add a unique contribution to the literature on retention of professional child welfare workers and the utility of Title IV-E social work training programs. While possession of an MSW did not have a significant influence on job satisfaction, it was significantly and negatively associated with ITS. However, the strength of association was much stronger for the non-Title IV-E group. In other words, those with the MSW degree who were non Title IV-E recipients were less likely to report intention to stay than their IV-E counterparts or workers who did not hold the MSW degree. Therefore, to the extent PCW administrators and managers are interested in hiring MSW graduates, those who received a Title IV-E stipend could be more likely to remain on the job. Moreover, the final model revealed BSW holders in rural areas tend to express higher job satisfaction and ITS. Accordingly, administrators and managers in rural areas could boost agency retention by recruiting BSW candidates.

Professional development.

According to this study's findings, professional development is an important workplace factor for administrators and managers to consider for boosting job satisfaction and retention. As discussed in Chapter 2, professional development generally refers to opportunities for promotion, professional growth, and opportunities for training, which prior research has generally – but not conclusively – found to be beneficial for turnover and job satisfaction. What was largely unexplored, however, is whether any differences existed between Title IV-E recipients and non-recipients in this regard. This study's findings generally comported with prior literature, indicating professional development opportunities are important for both job satisfaction and ITS, and equally so among both recipients and non-recipients of Title IV-E stipends. Although the influence of professional development was completely mediated by job satisfaction,

indicating it only indirectly influences ITS, the effect size listed in Table 9 (0.11) is as large or larger than many of the other factors that directly bear upon ITS.

Clark et al. (2013) offered several suggestions how managers could enhance professional development opportunities within their agencies, including providing support and incentives for licensure, promoting from within the agency or, conversely, offering recognition and incentives for so-called master social workers, who have achieved a high degree of technical competence in the field but might not want to switch to a supervisory role. Clark et al. also suggested agency managers should poll their employees on the types of training and development opportunities they would value the most.

One innovative approach to professional development appearing in the literature is diversity in work assignments. For example, rather than viewing the transfer of workers from a frontline PCW role to another role within a larger agency as “job hopping,” an undesirable sort of internal turnover, Samantrai (1992) stated job rotation could reduce problems associated with burnout among frontline workers. Willis et al. (2016a) concurred, stating cross-training employees in different areas of the organization allows workers to rotate through high turnover areas. From a development perspective, this type of intervention would “give [workers] an opportunity to feel success and achievement on a different level than service provision and would offer a welcome diversion from the daily trials of public child welfare” (Reagh, 1994, p. 76). Furthermore, it would also help workers to evaluate different job assignments (e.g., intake, ongoing casework) to determine which is the best fit for them in terms of skills, interests, and duties (Rycraft, 1994).

Social integration.

Table 9 shows an overview of the influence of three items related to social integration: coworker respect (item 25.3), work unit cohesiveness (item 25.4), and supervisor relations (a parcel of items 25.1 and 25.2). Coworker respect had a perhaps counterintuitive influence on ITS: higher levels of perceived coworker respect were associated with *lower* ITS and job satisfaction. As discussed in Chapter 2, Hopkins et al. (2010) and Boyas et al. (2011) found similar results. These authors surmised coworkers can encourage attitudes and behaviors that are helpful or harmful to organizational goals: “In some cases, especially those where there is constant stress and pressure as in child protection, social relationships can encourage the beginning of adverse social attitudes and behaviors, such as departing from the organization” (Boyas et al., 2011, p. 59). Thus, managers and administrators are wise to pay attention to the norms, values, and assumptions prevalent among PCW workers in their charge, because these will be mutually reinforced and transmitted to new members as an important aspect of the organization’s culture, or “a pattern of basic assumptions . . . invented, discovered, or developed by a given group . . . as it learns to cope with its problems” (Schein, 1990, p. 111). Workers who feel unsupported by organizational systems and their leadership teams are likely to turn to one another for support, at least until they have an opportunity to pursue other career options.

Interestingly, the item asking about work unit cohesiveness (25.4) did not function like the coworker respect item (25.3). These items clearly tapped into distinct constructs. It could be the word “cohesive” implies a degree of unity that results in organization effectiveness, and was therefore associated with higher ITS and job satisfaction. It is probably reasonable to recommend managers pay attention to work team unity and cooperation, as this dimension of the workplace

environment likely bears upon job satisfaction and ITS, and to an equal degree for Title IV-E stipend recipients and non-recipients.

Moreover, the supervisor relations parcel generally performed as expected, with workers perceiving higher levels of supervisor respect and support also tending to express higher ITS, although this relation was completely mediated through job satisfaction. That is, better supervisor relations predicted higher job satisfaction, which in turn predicted higher ITS, but perceived quality of supervisor relations did not have an independent effect on ITS. However, the influence of supervisor relations was less contingent than expected based on the literature review. To wit, employment duration did not moderate the influence of supervisor relations as suggested by Boyas et al. (2013) and Curry et al. (2005), nor did position (as manager or supervisor) serve as a moderator, as suggested by Johnco et al. (2014). Furthermore, the influence of supervisor relations did not differ for Title IV-E stipend recipients and non-recipients, contrary to findings from Rao Hermon et al. (2018) and Barbee et al. (2018).

The present study's results indicate managers and administrators could increase job satisfaction and ITS through interventions designed to increase workers' perceived quality of relations with their supervisors. Several scholars have offered insights about how this might be done. Samantrai (1992) stated agencies should not permit supervisory styles that are counterproductive, and should hold regularly scheduled development sessions. Zinn (2015) argued agencies should not only teach supervisors the technical aspects of effective supervision, but also emphasize the importance of the relationship with subordinates as the conduit through which supervision is delivered. Zinn also emphasized organizational processes and incentives should serve these goals, as supervisors will not be able to implement new knowledge gained about effective supervision if the organizational context is not conducive. Mor Barak, Travis,

Pyun, and Xie (2009) echoed these recommendations, suggesting supervisory training should cover task assistance (i.e., how to help frontline workers accomplish their basic jobs) as well as social/emotional support and interpersonal interaction, and that agencies should modify their policies to foster best practices, such as outlining the frequency at which supervisors are expected to meet with their charges. Renner, Porter, and Preister (2009) concurred face-to-face meetings at regular intervals are important components of effective supervision, helping to increase communication of policies, reinforcing training content, and fostering workers' perceptions of being included. Dickinson and Painter (2009) summarized the skills supervisors need to aid in retaining frontline workers:

Retention-focused supervisors know best practices with families, set clear and measurable performance expectations, and provide workers expert help through such tactics as coaching, case consultation and mentoring. Supervisors also help workers develop professional development plans and career paths that build on workers' skills. (p. 204)

Mor Barak et al. (2006) also offered several recommendations on how to improve supervision in PCW organizations, including basing promotions to supervisory positions on objective, job-related measures rather than seniority or office politics. Rycraft (1994) took a more charitable view, stating supervisors are often selected because of outstanding caseworker skills. Nevertheless, she came to the same conclusion as Mor Barak et al., noting the supervisory role requires a different skill set, and therefore robust supervisor selection processes as well as development programs are important for improving the quality of supervision in PCW. She concluded, "When guided and encouraged by the agency, [workers' initial interest in PCW]

develops into both a sense of mission and a commitment and dedication to the protection of children and strengthening of families” (Rycraft, 1994, p. 94).

Work-related self-efficacy.

Self-assessed work self-efficacy is an especially interesting area in terms of comparing the groups. Regardless of Title IV-E status, those who felt their university education prepared them for a career in PCW also expressed greater intentions to remain employed in PCW, although this factor had no influence on job satisfaction. While casework skills had no influence on job satisfaction for either group, Title IV-E recipients who felt more confident in their casework skills also expressed higher ITS, but this factor had no import for non-recipients. Furthermore, this emerged as one of the most important (in terms of effect size) retention factors for Title IV-E recipients (only job satisfaction was more important). In addition, while disabled/special needs skills were equally important for both groups’ job satisfaction, which indirectly increased ITS, these skills also had a direct influence on ITS, but only for Title IV-E recipients.

Table 9 provides an overview of the disparate influence of work self-efficacy within each group. The indirect influence of item 27.1 (university preparation) was not significant but the total influence (i.e., the summation of direct and indirect effects) did achieve significance, indicating this factor does increase ITS, but not via increasing job satisfaction. Also note the effect is the same in both groups, and the effect size is not particularly large (0.08 on a five-point scale) compared with other factors. In contrast, the total and indirect influences of casework skills and disabled/special needs skills within the non-recipient group are either non-significant or significant but of small effect size, but are significant with relatively large effect sizes in the Title IV-E group.

These results seem to comport with Rao Hermon et al.'s (2018) finding that Title IV-E recipients who had left PCW had lower self-efficacy than non-recipients who left. It appears self-efficacy is a particularly important retention factor for Title IV-E recipients, even after controlling for the degree to which respondents felt their university educations prepared them for PCW. This has important implications for managers and administrators: interventions designed to increase job-related skills might be particularly effective hedges against turnover for workers who had received a Title IV-E stipend, although this appears not to be the case for non-stipend recipients. Even disabled/special needs skills, which are important job satisfaction and retention factors for all workers, are particularly salient for Title IV-E recipients.

Position/job type.

As discussed in Chapter 2, prior research regarding the influence of position/job type on job satisfaction and turnover in PCW is mixed, but several studies indicated position/job type could influence these outcomes, and furthermore that this influence could be contingent on other factors. For instance, Chenot et al. (2009) found the influence of position was a function of employment duration, and Lizano and Mor Barak (2015) found evidence those with specialized child welfare training were more satisfied being supervisors rather than line workers, although this trend was not seen among workers without the specialized training. Results of the present study did not confirm any of these contingencies. Supervisors and managers did not express different levels of job satisfaction or ITS vis-à-vis their frontline colleagues, and this pattern was the same for Title IV-E recipients and non-recipients alike.

Assuming these findings comport with true population effects, and assuming the results of this study – which occurred within one agency – generalize to other agencies, then one implication for administrators and managers is they might not be able to assume supervisors' job

satisfaction and ITS are higher than frontline workers. As discussed in the literature review in Chapter 2, substantiated by findings in this study, supervisory relations are an important factor in job satisfaction and ITS. High turnover in the ranks of supervisors could have a compounding effect by catalyzing additional turnover among frontline workers (Smith, 2005), and Title IV-E workers may be no less susceptible to these dynamics.

Demographic factors.

Worker age directly influenced ITS (even after controlling employment duration, as discussed above), with older workers expressing more positive sentiment toward remaining employed at the agency, and this trend was not moderated by Title IV-E stipend status. This is generally in line with findings from previous research, as discussed in Chapter 2, along with recommendations managers and administrators should consider developing interventions specifically targeted at younger workers (e.g., Boyas et al., 2011; Boyas et al., 2015). However, it is also important to note ITS was not higher in older workers because they were more satisfied; indeed, age had no influence on job satisfaction. Therefore, managers and administrators should not presume just because a particular worker is older (independent of work experience), then that worker will tend to remain employed because they are more satisfied. (This trend is particularly noteworthy since the influence of employment duration, discussed above, followed the same pattern.) This raises the specter of employees remaining despite dissatisfaction, perhaps feeling trapped in their jobs (Smith, 2005). Job dissatisfaction does not always culminate in quitting, instead being manifest in other ways, such as work withdrawal (Hom et al., 2017).

Implications for Policy

Role overload.

As discussed in Chapter 2, PCW workers generally respond negatively to excessive workload, especially when it is driven by paperwork-related duties or other tasks that might detract from building relationships and serving clients. An assertion was also made in Chapter 2 that if the findings in the present study revealed role overload had less importance for job satisfaction and ITS for Title IV-E recipients, this would provide evidence Title IV-E recipients were perhaps more inured to the rigors of PCW work. However, Table 8 reveals this is not the case, as lower perceptions of role overload were associated with higher ITS, indirectly via job satisfaction, and this effect was the same in both groups. Thus, while findings from Jacquet et al. (2008) and Curry et al. (2005) indicated certain factors (such as commitment or capability) might buffer the influence of high workload, it appears policymakers should not assume Title IV-E training provides special protection from the ill effects of the perception of having too much work.

Compensation.

Tables 8 and 9 reveal salary satisfaction had significant influences on both job satisfaction and ITS. Furthermore, the influence on ITS was both direct and indirect, via job satisfaction, and the effect size of the total influence is comparable to other attitudinal variables such as professional development, role overload, and social integration. Moreover, Title IV-E recipients and non-recipients placed an equal importance on salary satisfaction. Thus, as with role overload, Title IV-E education appears to play no ameliorating role against dissatisfaction with salary, contradicting findings by Jones and Okamura (2000), which suggested Title IV-E recipients could be less sensitive to salary dissatisfaction.

Salary satisfaction is clearly an important factor for job satisfaction and ITS, but no more so than several other workplace factors. It is doubtful workers enter the PCW field in pursuit of, or with the expectation of, high salaries. Ellett et al. (2007) were probably correct in their findings – based on qualitative interviews with PCW workers – that salaries drive turnover when they become non-competitive with comparable professions. On the other hand, policymakers looking for savings to offset the costs of Title IV-E, as suggested by Slater et al. (2018), will have to look elsewhere for these benefits, as they should not expect Title IV-E recipients to be satisfied with lower salaries.

Professional training (social work degree).

The preliminary findings of Carr et al. (2018), indicating MSW graduates express lower ITS only if they are non-Title IV-E recipients, were partially supported in the present study. In the 2018 analysis, the influence of MSW status was non-significant in the Title IV-E group; in the present analysis, the MSW indicator was significant in both groups (with MSW graduates expressing lower ITS), but the effect size was much lower in the Title IV-E group (-0.29 versus -0.50). Even though there is still a “penalty” for MSW graduates among Title IV-E recipients (i.e., MSW graduates tending to express lower ITS), the influence seems to be much less. From a policymaking perspective, this does provide some limited evidence the Title IV-E program enhances retention. However, whether this translates into (a) improved outcomes for children and families and (b) cost savings (after considering the expenditures on the training stipends) is unclear and beyond the scope of the present inquiry, but the next section contains a discussion of how future research efforts could begin to answer such questions.

Rural/urban location.

As discussed in Chapter 2, some prior empirical work (Collins-Camargo et al., 2012; Griffiths et al., 2017; Yankeelov et al., 2009) indicates urban PCW workers might have greater turnover intent than their rural counterparts. One encouraging finding in the present study, however, is that Title IV-E appears to provide a protective factor against this tendency. Within the non-Title IV-E group, rural respondents indicated significantly higher ITS than urban respondents, but the association was non-significant in the Title IV-E group. From a policy perspective this finding is important, as it reveals Title IV-E recipients might make more committed workers in urban settings where ample alternative employment opportunities might otherwise lure away employees (National Association of Social Workers, 2006).

Study Limitations and Implications for Future Research

While the present study offers some insights into potential differences and similarities between Title IV-E recipients and non-recipients, practical and policy implications must be interpreted in light of some important limitations. These limitations are addressed in detail below, including how they can be overcome in future research. Broadly speaking, probably the most substantive contribution of the present study is that it can form a template for future studies of PCW turnover causes and the potential influence of Title IV-E on this decades-old problem. The multiple-group SEM framework is a powerful tool to investigate complex phenomena such as this. Nonetheless, there are several important improvements that could be made while following this overall template. This section presents the limitations of the present study, with an emphasis on how these limitations might be overcome in future studies within the multiple-group SEM approach, which is flexible enough to permit simultaneous implementation of the following suggestions in future research efforts.

Excluded constructs.

One important limitation of the current study is the exclusion of constructs prior research has shown to be salient in questions related to PCW turnover. For instance, Chapter 3 contained a discussion on measurement of the dependent variable ITS. It was noted the wording of item 22.4 overcomes a limitation noted in studies by Strand et al. (2010) and Collins-Camargo et al. (2012), who were unable to differentiate respondents' whose turnover intent was driven by being very close to retirement age; this represents a confounding of preventable and unpreventable turnover. Although this was not a concern in the present study, the wording of item 22.4 does not provide any insight into why workers may or may not want to continue with the agency until retirement. For instance, do they plan to leave for a different position in PCW and, if so, should such a move be considered turnover (Clark et al., 2013)? Rao Hermon et al. (2018) stated these types of distinctions are important for capturing nuance and gaining insights into how Title IV-E might contribute to PCW retention. Following Landsman's (2001) example, one way the present study could have been bolstered in this regard is inclusion of a measure of occupational commitment, which refers to intent to remain in the PCW field overall, rather than in one particular agency.

Landsman's (2001) study also included a measure of organizational commitment (i.e., identification with and involvement in the organization), which she theorized is causally after job satisfaction and prior to ITS. Organizational commitment plays an important role in PCW turnover. In a review of the broader turnover literature (not limited to child welfare), Hom et al. (2017) found organizational commitment predicted a unique portion of variability in turnover, net of job satisfaction. Within the public sector (i.e., employees of government agencies), Balfour and Wechsler (1996) found commitment is important for managers to pay attention to, as

it is largely a result of organization-related factors rather than personal characteristics (e.g., position, employment duration). Within the field of PCW, Hwang and Hopkins (2015) found organizational commitment mediated the influence of organizational inclusion (similar to social integration) and turnover intentions, while Weaver et al. (2007) found higher organizational commitment was associated with both lower turnover intentions and actual job exit.

Interestingly, Song (2005) even found organizational commitment mediates the relation between fear of future victimization from client violence and turnover intentions.

Another important construct not included in the present study is burnout, which includes dimensions such as emotional exhaustion, a growing negativity in relations with others (e.g., clients), and an increasingly negative attitude toward oneself (e.g., low morale, withdrawal) (Maslach, 1982). In a sample of PCW workers, Charles (2017) found burnout positively related to both turnover intent and actual turnover, and research by Boyas and Wind (2010) linked burnout to other important constructs, including social integration, organizational commitment, and worker age. Kim (2011) concluded some aspects of burnout are particularly high among PCW workers vis-à-vis other types of social workers, and future research should investigate the potential role for social work education and training to prevent burnout among PCW employees.

Employees may exhibit behaviors short of quitting that can also hamper achievement of organizational goals. As discussed earlier in this chapter, when dissatisfied, disengaged workers remain employed at their agencies, performance can suffer (Hom et al., 2017; Smith, 2005). In fact, turnover of low-performing workers could ultimately benefit organizations (Ellett et al., 2007). As Willis et al. (2016a) explained, “Retaining workers for the sake of having low turnover rates can be more costly to organizations if workers are unmotivated, burned out, and/or lack goodness-of-fit”(p. 122). In a study based on interviews with system-involved children, Strolin-

Goltzman et al. (2010) reported worker turnover can have beneficial effects when clients perceive new caseworkers to be more attentive, engaged, and encouraging than previous ones. This comports with Williams and Glisson's (2013) finding that reduced worker turnover positively influenced client outcomes only when the culture of the agency encourages supervisors to focus on these outcomes and develop workers to help attain them. Future research on PCW turnover should expand the scope of inquiry to include measures of worker performance and client outcomes. In their literature review, Hartinger-Saunders and Lyons (2013) noted a dearth of studies connecting Title IV-E training to "improved outcomes for children and families, [such as] safety, permanence, and well-being" (p. 293). The approach outlined above would represent a major step toward addressing this shortcoming.

In addition to work-related dynamics, external factors can also influence PCW turnover. For instance, the present study contained no information on family-related issues, which can catalyze/hasten or mollify turnover (Hom et al., 2017; Willis et al., 2016a). Shier et al. (2012) found personal factors such as life satisfaction predicted turnover intent among PCW workers, independently of and with equal importance as occupational commitment. Family-related dynamics can also dampen beneficial effects of protective factors against turnover, such as job satisfaction and ITS. In semi-structured interviews, Samantrai (1992) discovered a weak link between job satisfaction and turnover for those respondents who felt trapped in their jobs by family commitments (e.g., single parents). In a study by Weaver et al. (2007), the authors noted divorced, separated, or widowed respondents were much less likely to leave the job compared with their married colleagues, yet they did not express greater ITS. External factors and workplace dynamics can also interact. Strolin-Goltzman et al. (2007) found work-life fit (e.g., schedule flexibility, agency commitment to worker safety) significantly predicted odds of

engaging in job search behaviors among urban PCW workers. Finally, broader economic factors such as availability of alternative employment in a particular locale may also contribute to PCW turnover (e.g., Faller et al., 2010); such factors may be readily incorporated into a multi-level modeling framework discussed earlier.

Organizational commitment, burnout, worker performance, and external factors such as family influences and economic conditions appear to play important roles in PCW turnover and should be included in future causal modeling efforts. Inclusion of these constructs would present a more holistic model of ITS, and therefore provide additional opportunities to identify possible differences between Title IV-E recipients and non-recipients.

Influence of race/ethnicity.

Piescher, LaLiberte, and Lee (2018) noted racial/ethnic disparities persist in the PCW system, evidenced by the fact that in 2014 Black children represented about 14% of children in the U.S. yet accounted for nearly 23% of the alleged victims in CPS. These authors stated one way of addressing this concern is recruiting and retaining more people of color in the ranks of PCW workers. Several scholars have tried to determine how race/ethnicity might influence worker outcomes like job satisfaction and turnover, as discussed in Chapter 2. But results of empirical studies about the influence of race/ethnicity on PCW job satisfaction and turnover are quite mixed, and significant findings are oftentimes not interpreted, or interpreted by different researchers in disparate, often mutually exclusive ways. However, in none of the cited studies were rural/urban location and Title IV-E status simultaneously controlled, as in the present study.

Thus, findings from the current study offer an opportunity to gain some insights to this phenomenon, although important questions remain. Firstly, unlike in the Piescher et al. (2018) study, the racial/ethnic composition of the Title IV-E recipients and non-recipients was nearly

identical (see Table 1). Secondly, the influence of race/ethnicity on job satisfaction and ITS were not significantly different across groups: in both cases, non-White respondents were less satisfied and exhibited lower ITS. Furthermore, inspection of Table 9 reveals the total effect size of the non-White binary indicator (-0.21) is one of the larger influences examined in this study. Finally, as shown in Table 5, in contrast to Kim and Hopkins (2017) and Lizano and Mor Barak (2015), the influence of the non-White indicator on job satisfaction did not depend on rural/urban location (subsequent exploratory modeling revealed the interaction effect was non-significant for ITS, as well). Thus, regardless of Title IV-E status and rural/urban location, non-White workers in the sample tended to express lower job satisfaction and ITS.

However, it is difficult to translate these findings into meaningful practice implications for policymakers or managers interested in increasing PCW workforce diversity because it is not known *why* non-White respondents had lower job satisfaction and ITS. As with findings from Faller et al. (2010), who concluded more research is needed before diversity-oriented recruitment/retention programs can be designed and implemented because they were unsure why minority workers expressed lower intent to stay in CW, the research design in the current study precluded untangling causal relations surrounding this issue. Imagining future research in the context of multi-level modeling, it could be that there are agency-level factors beyond rural/urban location that bear upon the relation between race/ethnicity and turnover-related constructs. One such factor is diversity climate, or the degree to which employees feel management is fair to minority employees in terms of hiring, promotion, and inclusion (Brimhall et al., 2014). These agency-level factors could moderate the strength of relations between race/ethnicity and important worker-level outcomes. Future research should take into account

such factors to gain additional insights into the mechanism by which race/ethnicity influence turnover and related outcomes.

Work-related self-efficacy.

One concerning finding is that item 27.1, or the degree to which respondents' university education prepared them for a PCW career, was not more strongly related to job satisfaction or ITS in the Title IV-E group. Given that Title IV-E degree programs consist of specialized courseware geared toward child welfare work, it would seem the association between item 27.1 and the outcome variables would be significantly stronger among respondents who received Title IV-E stipends. That this was not the case would indicate future researchers might want to examine Title IV-E programs in light of how they can better prepare graduates for PCW work. Given the variation that exists among Title IV-E programs, a first step toward investigating this question would be including indicators of the program in which respondents participated. This would permit examining main as well as interactive influences of participating in various programs, which could in turn illuminate program characteristics most salubrious for preparing students for the rigors of PCW work.

Measurement.

Use of single item measures.

One of the advantages of SEM is the potential to model with unobserved, latent variables, which are free from measurement error (Bollen, 1989). However, as discussed in Chapter 3, the present study featured the sole use of manifest variables, since estimation of latent variables requires multiple indicators per construct. Thus, the current study was limited to multiple-group SEM with manifest variables, or path analysis. While using single-item measures is often necessary when measuring many constructs to keep questionnaire length reasonable, this practice

is not without limitations. In a meta-analytic path analysis, Tett and Meyer (1993) found turnover intentions mediated the influence of organizational commitment on actual turnover, but only when multi-item turnover intent measures were used. When single-item measures were used, the mediation effect disappeared. Lower reliability associated with single-item measures can attenuate correlations among constructs and bias structural parameter estimates in an unknown direction and magnitude (Berry, 1993), complicating interpretation of path analytic models (Cole & Preacher, 2013).

Restriction of range.

Another measurement limitation of the current study was the use of 5-point Likert scales. When using ordinal measures such as Likert scales, seven or more categories are recommended so the variables' distributions will comport more closely to normal theory statistical methods (Tabachnick & Fidell, 2013). Furthermore, in the present study some items displayed a restricted range of responses, with the preponderance of endorsements falling into only three of the five categories. Such restriction of range hampers item variance, and therefore covariance among items, which forms the basis for modeling statistical relations among constructs. Using items with better psychometric properties and at least seven response anchors – along with designating several items per construct, as recommended above – will enhance response variance and covariance, thus increasing effect sizes and statistical power.

Intent to stay (ITS).

Measurement of ITS was discussed at some length in Chapter 3 and elaborated above in the section titled *Excluded constructs*. Recall the decision was made to use solely item 22.4, pertaining to respondents' intent to remain employed at DFPS until retirement. As previously discussed, the strength of this item is the ability to distinguish between turnover intentions driven

by retirement and undesirable, preventable turnover driven by a desire to obtain alternative employment prior to serving out a career in PCW. On the other hand, it might be an unreasonable expectation for workers to remain employed in the same PCW agency all the way until retirement. As discussed above in *Excluded constructs*, including occupational commitment in future structural equation models will help address this issue. Moreover, use of a multi-item scale to capture a more holistic picture of turnover intention would also be beneficial. Two examples of such instruments are the Intent to Leave Child Welfare Scale (Auerbach et al., 2014) and the Intent to Remain Employed – Child Welfare scale (Ellett, 2000).

Yet another aspect of the measurement of turnover is the optimum number of years for a worker to remain in PCW, as discussed by Willis et al. (2016a). The authors stated stresses associated with PCW work can have deleterious effects on employees over time, raising questions about realistic or ideal timeframes for employment duration. Future researchers could begin investigating this important question by including measures of worker performance, as discussed previously, with an eye toward a drop-off in worker effectiveness after a number of years of service.

Role overload.

Since caseload itself is a function of many factors, some of which are probably not easily influenced, it might be more fruitful for managers and administrators to focus on the composition of tasks that make up frontline workers' overall workload. For instance, McGowan et al. (2009) found paperwork burden as strong a predictor in a multivariate model of turnover intentions, and qualitative results from Jacquet et al. (2008) indicate PCW workers often feel administrative tasks get in the way of doing "real social work." Future research should include at least two measures of role overload, including tasks that are directly related to providing client services as

well as ancillary tasks. This could provide more insightful, specific implications for managers and administrators, possibly helping them redesign work processes or reallocate duties.

Summary.

In sum, the study was limited by single items representing constructs, five-point Likert scales, and some poorly performing items that did not elicit much variability in responses. Using items from established scales would serve to ameliorate all these problems, albeit at the expense of a longer survey. As is evident from the discussion in Chapter 2, the PCW turnover literature suffers from a lack of consistent findings, making it frustratingly difficult to come to any consistent conclusions. Strolin-Goltzman et al. (2006) concurred, stating scales with at least some level of psychometric reliability and validity are preferable to “makeshift surveys”:

[The PCW turnover] literature is dense with inconsistencies and discrepancies, possibly due to the lack of standardized instruments available for measuring the individual, supervisory and organizational causes of turnover in a consistent manner. Clear, consistent, and validated measures of individual, supervisory and organizational factors that may relate to child welfare workforce turnover could facilitate a clearer and more consistent picture of the causes of turnover, and a more coherent framework upon which organizational interventions can be built. (p. 46)

Multi-level modeling.

When units of analysis (e.g., survey respondents) are hierarchically nested into larger units (e.g., students nested within classrooms, nested within schools), using standard regression-based techniques is problematic for two reasons. Firstly, standard error estimates will likely be biased due to violation of one of the basic assumptions of multiple regression: independence of errors (Keith, 2006). This means the degree of accuracy for predicting the outcome on any

particular subject in the analysis should not be correlated with the degree of accuracy for any other subject. This assumption is frequently violated when subjects are nested in some type of group, since the prediction errors of subjects within a particular group are likely to be more closely aligned with each other than with the errors of subjects in another group. This occurs because of group-level dynamics that operate somewhat independently of individual-level characteristics, or that may be conceptualized as the combined effect of all individuals in a particular group, which differs from other groups.

Taking into account this clustering effect is important for obtaining unbiased standard errors (de Leeuw & Meijer, 2008). For example, Rosenthal and Waters (2006) used a multi-level survival analysis (so-called frailty model) to study actual retention of PCW workers. They checked for group-level differences in regression parameters (i.e., intercepts and slopes) when taking into account how workers were nested within counties and supervisor work teams, respectively, and the standard errors their model produced took into account the clustering of individuals.

Secondly, there may be group-level variables that influence or explain individual-level outcomes (Raudenbush & Bryk, 2002). For example, consider a study by Kruzich et al. (2014), which featured an analysis of both individual (worker)-level and team-level (groups of employees working under the same supervisor) influences on turnover intentions. One of the main explanatory variables in the study was team psychological safety, which they defined as a “shared belief that the team is a safe environment for interpersonal risk taking” (p. 21). Note that, unlike all the explanatory variables in the present study, team psychological safety is a group-level variable, with each group’s mean likely varying from group to group. This so-called level two variable can be used in concert with level one (i.e., individual workers) variables to explain

phenomena of interest. Level two variables can even be used to explain differences in the strength of level one predictors if they are different from group to group (i.e., cross-level interactions). Another example is a study by Williams and Glisson (2013), who demonstrated reduced turnover was linked to improve case outcomes only in those instances where organizational culture (a level two variable) supported norms prioritizing client wellbeing and worker competence.

To overcome these problems, researchers working with hierarchically nested data can use multi-level modeling (MLM; also called hierarchical linear modeling or mixed linear modeling). In the present study, most workers were nested within specific offices, locations, or teams, but this information was not available to include in the analysis. This is a limitation of the study, since mean levels of the dependent variables (i.e., job satisfaction and ITS) may vary across locations or teams, as may the strength of relations between explanatory variables and dependent variables. In addition, there could be work team-level or location-specific characteristics that influence the dependent variables, such as local economic factors (e.g., availability of alternative employment) or the work environment at a particular office (e.g., influences of a particular culture or leadership style at the local level).

A few prior PCW turnover researchers have used some type of MLM, and results have been mixed in terms of how much variability occurred at the higher level. For instance, in a study of 1,460 PCW and private CW caseworkers in Illinois, employees' perception of job satisfaction was found to vary little across work teams and agencies (Zinn, 2015). Similarly, in Hwang and Hopkins' (2012) study, county membership explained only about 9% of the variance in turnover intent, and Rosenthal and Waters (2006) found the hazard rate for termination in their sample of PCW workers in Oklahoma varied little by clustering at the supervisor or county

levels. On the other hand, Glisson et al. (2012) found non-trivial variation at the organization level for several important predictors of job satisfaction. Moreover, results from a few other studies that did not employ MLM nevertheless suggest the presence of salient factors at a level above the individual worker. For instance, in Landsman's (2002) study of ITS and job satisfaction, rural/urban location was not a significant factor after controlling for the number of employees at the specific agency location. In a study of Title IV-E MSW graduates, Benton and Iglesias (2018) discovered work unit-level norms and policies can restrict work self-efficacy regardless of workers' background or training. Because PCW workers are nested within agency locations and work teams, contextual factors can emerge and are important considerations for future researchers. The multiple-group SEM framework used in the present study can be extended to include multi-level modeling.

Methodological limitations.

Cross-sectional design.

Although path analysis is a type of so-called causal modeling, it does not permit testing strong causal assumptions, especially using cross-sectional data (Asher, 1983). Many phenomena related to job satisfaction and turnover are dynamic (Chen, Ployhart, Thomas, Anderson, & Bliese, 2011; Hom et al., 2017; Liu, Mitchell, Lee, Holtom, & Hinkin, 2012), and these processes cannot be fully investigated using cross-sectional research methods. To make stronger causal claims, for example, using the term "mediation" rather than "indirect effects," it is necessary to have at least two and preferably three measurement occasions (Little, 2013). In this way, prior levels of mediator and outcome variables are controlled for. The multiple-group SEM framework readily accommodates longitudinal study designs.

Generalizability.

All data for the present study were collected in one state-based child welfare system across one southern state in 2008, which could present challenges for generalizability of results to other states or jurisdictions. One potentially mitigating factor is the similarity of the study sample to a nationally-representative sample of social workers (Dowd et al., 2014), at least in terms of age, employment duration, male/female split, and racial/ethnic composition. Despite this fact, some cell sizes were particularly small, and could have led to idiosyncratic results. As shown in Table 1, only 7% ($n = 53$) of non-Title IV-E respondents held MSW degrees, and there were only 29 male Title IV-E respondents, even though the proportion (12%) was comparable to both the non-Title IV-E group and the nationally-representative sample mentioned above.

Moreover, the target system was in a state of flux during the year of data collection (*A better understanding of caseworker turnover within child protective services*, 2009). In response to several years of instability and high turnover, in 2006 the agency implemented a variety of interventions, including improved training, a mentoring program, and technology improvements. By 2008 the organization was experiencing lower turnover and improved job-related employee attitudes, and alternative employment opportunities were drying up owing to the economic recession. Consequently, the agency was transitioning through a unique time in its history, and this could have influenced study participants' responses to survey questions.

Limitations of survey research.

The usual concerns about social desirability bias in self-reports (Phillips & Clancy, 1972) are applicable to the present study. The cover letter (see Appendix B) assured participants of confidentiality and voluntary participation, and explained only summary data would be available to managers, but it is nevertheless possible some responses were biased due to potential reprisals

from management. In addition, owing to the voluntary nature of the survey, it is possible non-respondents differed in some systematic way from respondents (e.g., higher levels of dissatisfaction, lower ITS, workload that precluded responding) (Westbrook, Ellett, & Asberg, 2012). Survey research is also subject to single source and single method bias, since the same source (i.e., the respondent) supplies information about both explanatory and outcome variables, and both types of variables are measured using the same method (in this case, five-point Likert scales) (Schwab, 2005).

Statistical power.

Results of a Monte Carlo post hoc power analysis were discussed in detail in Chapter 4; the discussion now turns to several implications that may be drawn from this analysis. Tables 10a and 10b reveal several important considerations for future research. For regression parameters within the non-Title IV-E group, the estimates with low power (i.e., below 0.8) are generally characterized by very low effect sizes. The cause of low power is probably not inadequate sample size; rather, it is likely low effect size, caused either by trivial true effects in the population or measurement error. As discussed previously in this chapter, measurement error tends to attenuate the strength of relations among constructs. Future research should use the best practices outlined previously for measurement; this will allow a determination to be made whether these constructs are important to retain in future studies. Excluding constructs with trivial effect sizes would be beneficial because the resulting model is simpler, leaving more statistical power for detecting other effects.

Within the Title IV-E group, there is at least one regression parameter with a non-trivial effect size (MSW status) that does not meet the recommended power threshold of 0.8. Furthermore, Table 10b reveals power was inadequate for most of the group differences in

regression parameters. Taken together, these facts indicate the sample size in the Title IV-E group was too small, and there was too much of an imbalance in the group sizes. Future researchers should aim for 1,000 to 1,500 respondents, with the samples more closely split between Title IV-E recipients and non-recipients. Such a sample should be sufficient, provided other best practices listed above are also followed.

Summary and Conclusion

Chapter 1 began with a brief summary of the history of PCW turnover, its associated costs (both financial and human), as well as the government's use of Title IV-E training stipends as an intervention to stem unwanted turnover. It was also mentioned that the Family First Prevention Services Act could cause funds for training stipends to be diverted without robust empirical evidence of the program's effectiveness. The discussion then moved to the paucity of prior research into the influence of Title IV-E training stipends on PCW turnover. The literature review identified only seven studies explicitly investigating this topic since 1984, of which only three employed multivariate statistical techniques that could account for confounding effects.

In a previous study using the same dataset as the present investigation, Carr et al. (2018) demonstrated Title IV-E training could bolster retention of MSW graduates. Specifically, in that study MSW graduates tended to express lower ITS, but only among non-Title IV-E recipients; within the Title IV-E group, there was no significant association between MSW status and ITS. Nevertheless, these results were exploratory since a multiple regression framework was used, meaning possible causal relations among explanatory variables were not considered. The present study extended Carr et al.'s (2018) work by incorporating a causal modeling approach, wherein explanatory variables' influence on ITS was examined using job satisfaction as a mediating variable.

In Chapter 2, the investigator presented an overview of the literature on PCW turnover for the past few decades. Although there were few studies specifically assessing the influence of Title IV-E as a protective factor for turnover, it was important to identify other influences on PCW turnover in order to specify a comprehensive model of turnover intent. These influences were sorted into several categories, including employment duration, professional training (social work degree), professional development, social integration, role overload, work-related self-efficacy, compensation, position/job type (i.e., frontline versus supervisory), job satisfaction, and demographic characteristics (including rural/urban location, race/ethnicity, age, and gender). For most of these categories, the influence on job satisfaction and turnover-related constructs was unclear based on mixed findings in prior empirical studies. The investigator hypothesized one main reason for inconsistent results across studies is a generally weak level of methodological and statistical rigor in this field of inquiry, although several exceptional studies were mentioned. One such exceptional study was Landsman (2001), whose structural equation model served as the basis for the conceptual model used in the present analysis, which followed the logic that distal causes of turnover are mediated by more proximate causes.

Chapter 3 outlined the methodological approach taken in the present study. The statistical foundation was multiple-group structural equation modeling (SEM) with manifest variables, also known as path analysis. SEM was chosen not only because it could provide the most appropriate framework for the present study, but also it is an extremely flexible approach that can accommodate all recommendations for future research outlined in Chapter 5. In the present study, SEM provided a means to test a causal model of turnover intent, whereby distal explanatory variables (worker characteristics, salary satisfaction, professional development satisfaction, social integration, role overload, professional training, and work-related self-

efficacy) influenced ITS directly and/or indirectly via job satisfaction (see Figure 2). Moreover, direct and indirect effects for this causal model were estimated separately for each group (based on Title IV-E stipend status) in a combined analysis, with each estimate being statistically compared across groups; significant differences provided evidence the Title IV-E grouping variable served to moderate the effect in question. In addition to the usual details regarding estimation, missing data handling, and basic multivariate assumptions, Chapter 3 also outlined the model building process employed to arrive at the most parsimonious model that adequately explained relations among the variables.

Chapter 4 presented a technical interpretation of findings from preliminary models, the final model, details about how competing models were tested, and associated model diagnostics. Findings presented in Tables 8 and 9 were discussed in detail, with descriptions of how parameter estimates are properly interpreted. It was shown that several variables indirectly influence ITS through job satisfaction, but also that none of indirect paths vary significantly across groups. All of the significant group differences were found within the direct effects. Namely, it was found that only among Title IV-E workers did higher levels of prior social service experience correspond to higher ITS. In terms of work-related self-efficacy, casework skills and skills working with disabled/special needs clients were salient predictors of ITS only for Title IV-E recipients. Rural workers expressed higher ITS only among non-Title IV-E recipients, although the group difference did not achieve statistical significance. Similarly, the negative influence of possessing an MSW degree was somewhat less among Title IV-E recipients. Finally, male respondents tended to express lower ITS, but only among Title IV-E recipients. On the other hand, many effects were not different across groups, including employment duration at current agency, satisfaction with professional development, the role of

social integration, role overload, the influence of university-gained skills, salary satisfaction, job position/type, age, and race/ethnicity.

The practical implications of these findings were presented earlier in this chapter and need not be repeated here. However, it is important to interpret these results in light of the research objectives outlined in Chapter 1. The specific aims of this study were (a) to test a causal model of turnover intentions, whereby distal explanatory variables indirectly influence ITS through job satisfaction; and (b) identify group differences in the pattern of association within the causal model based on receipt of Title IV-E stipends. The proposed benefits of achieving these aims were identifying ways in which Title IV-E may bolster PCW retention as well as retention factors that matter most for Title IV-E recipients. It was stated if Title IV-E recipients appear less influenced by workplace challenges that are difficult for administrators and managers to ameliorate, this would provide evidence of the program's protective influence on turnover.

The results generally supported the notion of a causal model of turnover intent, as several of the indirect effects listed in Table 9 achieved statistical significance. Furthermore, several group differences were identified and some of these differences are indicative of Title IV-E's possible benefit in reducing turnover. For example, it is encouraging to see no significant difference in ITS of urban/rural respondents within the Title IV-E group, as this is an impossible factor for administrators and managers to influence. Perhaps most importantly, the effect size of MSW graduates expressing lower ITS was substantially lower for Title IV-E recipients. As previously mentioned, the proportion of MSW graduates in the non-Title IV-E group was low (7%), so more research is needed to verify this finding.

Other findings were not as encouraging from the standpoint of Title IV-E stipends providing a protective factor against PCW turnover. Title IV-E recipients appeared to be just as

susceptible to dissatisfaction with workplace factors such as professional development, social integration, role overload, and salary. One demographic-related finding was also troubling: among Title IV-E recipients, males had a tendency of reporting significantly lower ITS. However, as with non-Title IV-E MSW graduates mentioned in the previous paragraph, there was a small number of males within the Title IV-E group ($n = 29$), and the results could be idiosyncratic. More research is necessary to determine if this finding generalizes. More research is also necessary to determine why item 27.1, university preparation, was not more strongly related to job satisfaction and ITS in the Title IV-E group.

Taken together, the overall findings of this study are mixed in terms of the influence of Title IV-E on PCW retention. But several important limitations prevent drawing any hard and fast conclusions. For starters, the causal model of turnover intent was incomplete. Several important mediators of distal causes of turnover (e.g., Landsman, 2001) were excluded. There were also concerns with measurement, especially regarding the use of single items to measure constructs and restricted range of responses to some of the Likert items. Correspondingly, the Monte Carlo power analyses revealed statistical power was quite limited, especially for checking group differences (i.e., the difference in regression parameter estimates across groups). It was discussed that balancing group sizes (i.e., having more Title IV-E recipients), along with improving measures, would help achieve more power in future studies.

Informing future empirical research into the influence of Title IV-E on PCW turnover is probably the greatest contribution of the present study. The design of the study, together with extensive recommendations on how to mitigate the study's weaknesses, provide a robust template for future research. The multiple-group SEM framework is a powerful tool that can accommodate the conceptual and statistical extensions suggested in this chapter. A concerted

research program building upon this foundation would provide solid evidence of the effectiveness of Title IV-E in reducing PCW turnover, if such an effect actually exists. These findings could, in turn, be linked with measures of worker performance, including outcomes for system-involved children and families. A small fraction of Title IV-E funds could fund such an effort. Elucidating a more comprehensive, causal picture of the influence of the Title IV-E stipend program on intermediate and final PCW outcomes will reveal how this important program contributes to child welfare and how it might do so even more effectively in the future.

Tables**Table 1 Univariate Counts and Proportions for Categorical Variables**

Group Non-IVE (<i>n</i> = 716)			Group IVE (<i>n</i> = 253)		
Rural			Rural		
Yes	250	36%	Yes	81	33%
Male			Male		
Yes	105	15%	Yes	29	12%
Ethnicity			Ethnicity		
White	307	43%	White	116	46%
African Am./Black	231	32%	African Am./Black	81	32%
Hispanic	155	22%	Hispanic	48	19%
Other	20	3%	Other	7	3%
BSW			BSW		
Yes	136	19%	Yes	130	51%
MSW			MSW		
Yes	53	7%	Yes	123	49%
Manager or Supervisor			Manager or Supervisor		
Yes	239	34%	Yes	99	39%

Table 2 Univariate Descriptive Statistics for Continuous Variables

Variable	Valid n	Group Non-IVE					Valid n	Group IVE				
		Mean/ SD	Skewness/ Kurtosis	Minimum/ Maximum	% with Min/Max	Median		Mean/ SD	Skewness/ Kurtosis	Minimum/ Maximum	% with Min/Max	Median
Age		40.87	0.35	22.35	0.15%	39.63		38.06	0.60	22.68	0.42%	35.23
	670	10.59	-0.79	71.89	0.15%		240	10.12	-0.77	65.49	0.42%	
Employment Duration		8.92	1.06	0.08	1.68%	7.33		7.97	1.32	0.08	0.40%	6.58
	715	7.39	0.66	34.92	0.14%		251	6.47	1.65	32.75	0.40%	
Years Prior Social Service Employment		7.00	1.37	0.00	25.05%	4.00		5.54	1.69	0.00	30.46%	3.00
	467	7.88	1.44	36.00	0.21%		197	6.84	3.09	37.00	0.51%	
Years Prior Non-Social Service Employment		8.45	1.35	0.00	14.73%	6.00		7.09	1.48	0.00	17.39%	5.00
	414	8.32	1.77	45.00	0.24%		161	7.52	1.64	33.00	0.62%	
Salary Satisfaction (22.1)		2.25	0.59	1.00	28.99%	2.00		2.34	0.41	1.00	27.27%	2.00
	714	1.11	-0.71	5.00	1.96%		253	1.13	-1.06	5.00	1.19%	
Professional Development Satisfaction (22.2)		3.52	-0.87	1.00	4.40%	4.00		3.69	-0.97	1.00	2.37%	4.00
	705	0.99	0.17	5.00	9.50%		253	0.95	0.40	5.00	13.83%	
Job Satisfaction (22.3)		3.80	-1.11	1.00	3.78%	4.00		3.83	-1.26	1.00	3.97%	4.00
	715	0.95	1.22	5.00	19.16%		252	0.92	1.86	5.00	18.25%	
Retire from Agency (ITS) (22.4)		3.64	-0.61	1.00	6.81%	4.00		3.50	-0.51	1.00	8.37%	4.00
	705	1.13	-0.12	5.00	26.52%		251	1.17	-0.39	5.00	22.71%	
Respect from Supervisor (25.1)		4.23	-1.51	1.00	2.24%	4.00		4.17	-1.50	1.00	2.37%	4.00
	713	0.88	2.80	5.00	43.06%		253	0.88	2.84	5.00	37.55%	
Support from Supervisor (25.2)		4.13	-1.46	1.00	3.38%	4.00		4.06	-1.14	1.00	1.98%	4.00
	711	0.97	2.13	5.00	39.94%		253	0.94	1.19	5.00	34.78%	
Respect from Coworkers (25.3)		4.21	-1.11	1.00	0.56%	4.00		4.22	-0.76	2.00	2.37%	4.00
	713	0.73	2.43	5.00	34.78%		253	0.67	1.23	5.00	33.60%	
Work Unit Cohesive (25.4)		4.04	-1.18	1.00	2.71%	4.00		4.05	-1.30	1.00	3.19%	4.00
	702	0.97	1.24	5.00	34.90%		251	0.98	1.60	5.00	34.66%	
Accomplish Enough Work (26.2)		3.84	-1.08	1.00	4.49%	4.00		3.75	-0.97	1.00	4.78%	4.00
	713	1.07	0.57	5.00	26.79%		251	1.08	0.23	5.00	22.71%	
Job Resources Sufficient (26.3)		3.56	-0.78	1.00	6.89%	4.00		3.61	-0.81	1.00	5.14%	4.00
	711	1.14	-0.27	5.00	17.30%		253	1.09	-0.14	5.00	17.79%	
University Prepared Me (27.1)		3.50	-0.60	1.00	3.98%	4.00		3.79	-1.14	1.00	3.95%	4.00
	654	1.08	-0.56	5.00	14.37%		253	0.99	0.96	5.00	19.37%	
Casework Skills (28)		4.40	-1.68	1.00	1.54%	5.00		4.47	-0.86	2.00	0.41%	5.00
	651	0.81	3.61	5.00	55.15%		241	0.63	0.17	5.00	53.53%	
Administrative Skills (32)		4.25	-0.68	1.00	0.15%	4.00		4.17	-0.91	1.00	0.42%	4.00
	678	0.72	0.22	5.00	40.41%		240	0.77	1.14	5.00	35.42%	
Cultural Diversity Skills (34)		4.42	-0.86	1.00	0.14%	4.50		4.37	-1.00	1.00	0.40%	4.00
	702	0.65	0.69	5.00	50.00%		251	0.69	1.56	5.00	47.41%	
Disabled/Special Needs Skills (36)		4.03	-0.60	1.00	0.44%	4.00		4.05	-0.37	2.00	2.40%	4.00
	685	0.83	0.07	5.00	31.39%		250	0.81	-0.70	5.00	32.80%	

Note. Higher score on scale items indicates more favorable/positive attitude. Parenthetical numbers refer to corresponding item number shown in Appendix B. *SD* = standard deviation.

Table 3a Bivariate Correlations among Model Variables for Non-Title IV-E Group

Non- Emp.																											Supv. Ovld. Mgr./			
Age	Rural	Male	White	Dur.	BSW	MSW	Q21.1	Q21.2	Q22.1	Q22.2	Q22.3	Q22.4	Q22.5	Q22.6	Q25.1	Q25.2	Q25.3	Q25.4	Q26.1	Q26.2	Q26.3	Q27.1	Q28.1	Q32.1	Q34.1	Q36.1	Parcel	Parcel	Supv.	
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	
1	1																													
2	.09	1																												
3	.08	-.02	1																											
4	-.16*	-.40*	-.03	1																										
5	.59*	.02	0	-.16*	1																									
6	.13*	-.13	-.07	.04	.08	1																								
7	.25*	-.14	.05	.05	.20*	.52*	1																							
8	.50*	-.04	.06	-.09	.43*	.21*	.15*	1																						
9	.51*	.12	.13*	-.07	0	.07	.01	.04	1																					
10	.04	.06	.01	-.04	.06	-.04	0	.01	-.04	1																				
11	-.09*	-.10*	-.10	-.03	-.03	-.06	.05	.02	-.07	.29*	1																			
12	.05	.04	-.09	-.12*	.09*	.12*	.04	.11*	-.08	.33*	.54*	1																		
13	.44*	.19*	.06	-.23*	.38*	.12	-.07	.24*	.18*	.18*	.41*	1																		
14	.07	.12*	-.04	-.23*	.10*	.02	-.07	.02	.02	.10*	.21*	.35*	.50*	1																
15	.11*	.11*	-.06	-.18*	.06	.10	-.11	.02	.01	.17*	.21*	.32*	.56*	.66*	1															
16	-.10*	-.03	.07	-.09	-.05	-.04	-.01	-.03	-.05	.13*	.36*	.33*	.13*	.15*	.12*	1														
17	-.08*	.04	-.02	-.03	-.05	-.04	.02	-.08	-.05	.13*	.39*	.41*	.17*	.20*	.19*	.76*	1													
18	-.05	-.06	-.03	-.08	-.05	.03	.07	-.01	0	.06	.26*	.21*	.03	.08*	.05	.52*	.45*	1												
19	-.05	-.01	-.05	-.04	-.02	.09	.09	-.07	-.06	.12*	.31*	.35*	.17*	.19*	.19*	.48*	.55*	.54*	1											
20	-.09*	-.02	-.09	-.03	.02	.11*	.01	.07	-.09*	.17*	.43*	.41*	.16*	.18*	.17*	.42*	.43*	.40*	.41*	1										
21	.02	.06	.02	-.01	.04	-.01	.09	.04	.05	.19*	.28*	.33*	.24*	.16*	.16*	.33*	.32*	.20*	.25*	.46*	1									
22	-.07	.04	.07	.06	-.03	-.08	.05	-.06	-.05	.20*	.27*	.35*	.15*	.16*	.14*	.29*	.33*	.18*	.26*	.36*	.67*	1								
23	-.03	-.03	.12*	.08	-.05	.24*	.23*	0	0	.07	.14*	.18*	.08*	0	.05	.11*	.11*	.09*	.13*	.25*	.28*	.27*	1							
24	.16*	-.10*	.02	-.09	.28*	.14*	.15*	.18*	.01	-.04	.05	.08*	.15*	.09*	.08	.05	.03	.08*	.09*	.14*	.08*	.04	.14*	1						
25	.07	-.11*	.08	.16*	.07	-.02	-.02	0	.05	-.01	0	.04	.07	-.05	.02	.08*	.03	.11*	.11*	.11*	.20*	.18*	.15*	.27*	1					
26	.09*	-.09	.08	.28*	.01	0	0	.09	.11	-.05	.07	.02	-.01	-.07	-.04	0	-.01	.09*	.07	.07	.07	.14*	.30*	.34*	1					
27	.10*	0	-.01	.08	-.01	-.01	-.04	.10*	.02	-.03	-.03	.11*	.06	-.04	.02	.04	.01	.11*	.02	.08*	.06	.06	.11*	.24*	.22*	.47*	1			
28	-.10*	.01	0	-.05	-.04	-.03	-.01	-.04	-.07	.13*	.40*	.40*	.16*	.20*	.18*	.86*	.90*	.46*	.53*	.43*	.33*	.31*	.13*	.03	.04	-.03	.01	1		
29	-.05	.03	-.01	-.01	.02	.07	.06	.07	-.02	.25*	.42*	.46*	.23*	.22*	.18*	.40*	.44*	.30*	.38*	.77*	.77*	.53*	.30*	.09*	.14*	.02	.06	.46*	1	
30	.13*	-.07	.16*	-.21*	.36*	.17*	.24*	.25*	-.15*	.06	.16*	.17*	.24*	.26*	.21*	.02	0	-.07	.13*	.11*	-.05	-.05	.08	.40*	.12*	-.02	-.01	.04	.06	1

Note. Calculated in *Mplus* using tetrachoric (binary with binary), Pearson (continuous with continuous), and biserial (binary with continuous) correlations. Variables 2, 3, 4, 6, and 7 are binary; the remainder are continuous. * $p < .05$.

Table 3b Bivariate Correlations among Model Variables for Title IV-E Group

	Non- Emp.										Supv. Ovld. Mgr./																			
	Age	Rural	Male	White	Dur.	BSW	MSW	Q21.1	Q21.2	Q22.1	Q22.2	Q22.3	Q22.4	Q22.5	Q22.6	Q25.1	Q25.2	Q25.3	Q25.4	Q26.1	Q26.2	Q26.3	Q27.1	Q28.1	Q32.1	Q34.1	Q36.1	Parcel	Parcel	Supv.
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	1																													
2	-.09	1																												
3	.22*	.03	1																											
4	-.07	-.34*	.12	1																										
5	.61*	-.03	-.01	-.11	1																									
6	-.20*	.08	-.15	.09	-.23*	1																								
7	.30*	-.14	-.16	-.01	.49*	.02	1																							
8	.38*	-.14	.03	-.03	.39*	-.18	.25*	1																						
9	.42*	.09	.16	-.17	-.02	-.12	.16	.20*	1																					
10	-.05	.17*	-.09	-.07	.03	-.02	-.05	.02	.03	1																				
11	-.10	.07	-.04	-.06	-.12*	.02	-.07	-.09	.16*	.28*	1																			
12	.05	.03	-.05	-.03	.11	.07	.04	.02	.10	.37*	.48*	1																		
13	.44*	.04	-.09	-.20*	.42*	-.05	.13	.30*	.24*	.29*	.22*	.44*	1																	
14	.14*	-.08	-.14	-.16*	.08	-.01	-.06	.11	.19*	.14*	.13*	.28*	.47*	1																
15	.13*	.05	.10	-.16*	-.04	.07	-.25*	.04	.19*	.20*	.14*	.27*	.53*	.57*	1															
16	-.03	-.14	-.01	.05	.00	.02	.22*	.00	.12	.05	.18*	.23*	.12	.01	-.01	1														
17	-.05	-.09	.07	.09	-.04	.04	.18*	.02	.13	.11	.17*	.29*	.11	.07	.01	.82*	1													
18	-.04	.00	.03	.09	-.07	.05	.03	-.05	.21*	.09	.15*	.20*	.06	-.01	-.03	.49*	.40*	1												
19	.04	-.02	-.03	.04	.00	.01	.10	.00	.21*	.04	.20*	.20*	.10	.03	-.03	.46*	.51*	.50*	1											
20	-.07	-.03	-.04	.12	-.11	.07	.02	-.01	.22*	.07	.32*	.32*	.12*	.16*	.06	.38*	.29*	.41*	.31*	1										
21	-.01	-.03	.08	.07	-.05	.12	.13	-.09	.07	.06	.28*	.29*	.05	.13*	.06	.30*	.23*	.26*	.26*	.37*	1									
22	-.06	.02	.06	.08	-.08	.14	-.01	-.03	.12	.11	.29*	.36*	.16*	.15*	.16*	.33*	.26*	.33*	.29*	.44*	.70*	1								
23	-.01	-.12	-.06	.08	-.08	.12	.12	.03	.10	.13*	.24*	.25*	.16*	.11	.16*	.31*	.34*	.25*	.26*	.29*	.34*	.34*	1							
24	.15*	-.12	-.01	.05	.31*	-.03	.25*	.03	.06	-.04	.06	.11	.26*	.10	.00	.12*	.07	.09	.10	.15*	.14*	.19*	-.01	1						
25	-.03	-.03	-.09	.21*	-.08	-.08	-.01	.06	.07	-.04	.07	.07	.04	.06	-.03	.10	.00	.15*	.09	.21*	.20*	.26*	.03	.27*	1					
26	.16*	-.03	.20	.29*	.02	-.10	.04	.04	.01	.06	.01	.04	.07	.02	-.05	.00	.04	.01	.05	.09	.12	.13	.12	.18*	.32*	1				
27	.12	.09	.05	.03	-.01	.02	-.06	.05	.13	.12*	.13*	.12	.22*	-.04	.09	.07	.01	.09	.06	.08	.12	.11	.08	.17*	.26*	.52*	1			
28	-.06	-.10	.03	.08	-.03	.07	.24*	.01	.12*	.12	.19*	.29*	.12	.04	.02	.89*	.91*	.41*	.44*	.32*	.26*	.28*	.33*	.09	.01	-.01	.02	1		
29	-.05	-.02	.02	.03	-.06	.12	.14	-.05	.13*	.11	.37*	.37*	.12*	.18*	.09	.36*	.29*	.32*	.26*	.70*	.79*	.64*	.34*	.22*	.20*	.07	.09	.36*	1	
30	.20*	-.12	-.19	.10	.45*	.00	.23*	.17	.08	-.03	.10	.16*	.22*	.18*	.09	-.10	-.04	-.14	.02	.12	-.13	-.09	-.05	.42*	-.03	.03	-.12	-.05	.02	1

Note. Calculated in *Mplus* using tetrachoric (binary with binary), Pearson (continuous with continuous), and biserial (binary with continuous) correlations. Variables 2, 3, 4, 6, and 7 are binary; the remainder are continuous. * $p < .05$.

Table 4 Variance Inflation Factors by Group

	Non-IVE	IVE
Age	3.43	4.14
Rural	1.26	1.21
Male	1.16	1.33
Non-White	1.40	1.45
Employment Duration	2.38	3.74
BSW	1.22	1.30
MSW	1.30	1.62
Years Prior Social Service Employment	1.62	1.39
Years Prior Non-Social Service Employment	1.94	2.22
Salary Satisfaction (22.1)	1.20	1.44
Professional Development Satisfaction (22.2)	1.80	2.09
Job Satisfaction (22.3)	2.35	2.62
Retire from Agency (22.4)	1.85	2.94
Respect from Supervisor (25.1)	2.83	7.53
Support from Supervisor (25.2)	2.96	6.85
Respect from Coworkers (25.3)	1.83	1.71
Work Unit Cohesive (25.4)	2.09	1.57
Accomplish Enough Work (26.2)	2.25	2.91
Job Resources Sufficient (26.3)	2.16	2.76
University Prepared Me (27.1)	1.24	1.51
Casework Skills (28)	1.29	2.09
Administrative Skills (32)	1.32	1.40
Cultural Diversity Skills (34)	1.83	1.87
Disabled/Special Needs Skills (36)	1.65	1.93
Manager or Supervisor	1.36	1.91

Note. VIFs calculated using **car** package for R (Fox, 2002).

Table 5 Results of Preliminary Models Checking for Interaction Effects

Interaction Effect	DV	Reference(s)	Exploratory Results: Non-IV-E	Exploratory Results: IV-E
Age*Role Overload Parcel	ITS	Boyas et al. (2011); Cohen-Callow et al. (2009)	n.s.	n.s.
Age*Rural	ITS	Kim and Hopkins (2017)	n.s.	$p=.109$
Employment Duration*Age	ITS	Boyas et al. (2013); Curry et al. (2005)	n.s.	n.s.
Employment Duration*BSW	ITS	Chenot et al. (2009)	n.s.	n.s.
Employment Duration*BSW	JS	Scannapieco et al. (2012)	n.s.	n.s.
Employment Duration*Coworker Relations	ITS	Boyas et al. (2011); Chenot et al. (2009)	$p=.062$ for coworker respect; n.s. for work unit cohesive	n.s. for coworker respect; n.s. for work unit cohesive
Employment Duration*MSW	ITS	Chenot et al. (2009)	n.s.	n.s.
Employment Duration*MSW	JS	Scannapieco et al. (2012)	n.s.	n.s.
Employment Duration*Position (Supervisor or Manager)	ITS	Chenot et al. (2009)	$p=.133$	n.s.
Employment Duration*Rural	ITS	McGowan et al. (2009); Strolin-Goltzman et al. (2007)	n.s.	n.s.
Employment Duration*Supervisor Relations Parcel	ITS	Boyas et al. (2013); Curry et al. (2005)	$p=.048$	n.s.
Non-White*Rural	JS	Kim and Hopkins (2017); Lizano and Mor Barak (2015)	n.s.	n.s.
Position (Manager or Supervisor)*Supervisor Relations Parcel	ITS	Johnco et al. (2014)	n.s.	n.s.
Rural*BSW	ITS	Strolin-Goltzman et al. (2007)	n.s.	n.s.
Rural*BSW	JS	Kim and Hopkins (2017)	n.s.	$p=.121$
Rural*MSW	ITS	Strolin-Goltzman et al. (2007)	$p=.08$	n.s.
Rural*MSW	JS	Kim and Hopkins (2017)	n.s.	n.s.

Note. n.s. = non-significant.

Table 6 Summary of Model Building Process

Model Name	Description	Difference Testing Results	Interpretation
M1	Regression slopes constrained to equality across groups; residual variances freely estimated	N/A	N/A
M1.1	Regression slopes and residual variances constrained to equality across groups	n.s. when compared to M1	R^2 for both DVs are similar across groups
M1.2	Regression slopes freely estimated in both groups; residual variances constrained to equality	N/A	N/A
M1.2.1 (final model)	Regression slopes indicated by Wald or modification indices to be sig. (see Table 7) were freely estimated; other regression slopes and residual variances constrained to equality. This is the final model whose results are indicated in Tables 8 and 9.	n.s. when compared to M1.2; sig. when compared to M1.1	These multiple degree of freedom tests supported results from Wald tests and modification indices in terms of which regression slopes varied across groups and which did not

Table 7 Wald Tests and Modification Indices Checking Differences in Regression Slopes across Groups

Regression Slope	Difference in Slopes	Std. Error of the Difference	z Statistic	p-Value of Difference	Modification Index
ITS on Age	0.006	0.013	0.427	.67	
ITS on Position	0.193	0.149	1.297	.20	
ITS on Rural	0.270	0.138	1.954	.05*	
ITS on Gender	0.441	0.195	2.265	.02*	
ITS on Non-White	0.051	0.133	0.380	.70	
ITS on Employment Duration	0.024	0.017	1.409	.16	6.015
ITS on BSW	0.037	0.135	0.271	.79	
ITS on MSW	0.196	0.187	1.045	.30	4.057
ITS on Years Prior Social Service Employment	0.017	0.011	1.583	.11	5.891
ITS on Years Prior Non-Social Service Employment	0.024	0.016	1.555	.12	
ITS on Salary Satisfaction (22.1)	0.087	0.061	1.422	.16	
ITS on Professional Dev. (22.2)	0.034	0.096	0.351	.73	
ITS on Job Satisfaction (22.3)	0.054	0.108	0.501	.62	
ITS on Coworker Respect (25.3)	0.089	0.104	0.852	.39	
ITS on Work Unit Cohesive (25.4)	0.104	0.079	1.310	.19	
ITS on University Prepared Me (27.1)	0.046	0.069	0.669	.50	
ITS on Casework Skills (28)	0.314	0.106	2.976	.00*	9.660
ITS on Disabled/Special Needs Skills (36)	0.119	0.082	1.450	.15	4.536
ITS on Supervisor Relations Parcel	0.022	0.094	0.237	.81	
ITS on Role Overload Parcel	0.206	0.127	1.619	.11	
ITS on Age*Rural	0.024	0.013	1.810	.07	
JS on Age	0.008	0.012	0.686	.49	
JS on Position	0.054	0.125	0.436	.66	
JS on Rural	0.217	0.148	1.466	.14	
JS on Gender	0.128	0.162	0.791	.43	
JS on Non-White	0.059	0.106	0.558	.58	
JS on Employment Duration	0.018	0.014	1.246	.21	
JS on BSW	0.172	0.144	1.194	.23	
JS on MSW	0.071	0.161	0.438	.66	
JS on Years Prior Social Service Employment	0.009	0.011	0.833	.41	
JS on Years Prior Non-Social Service Employment	0.001	0.012	0.084	.93	
JS on Salary Satisfaction (22.1)	0.076	0.048	1.597	.11	
JS on Professional Dev. (22.2)	0.045	0.08	0.570	.57	
JS on Coworker Respect (25.3)	0.143	0.089	1.610	.11	
JS on Work Unit Cohesive (25.4)	0.019	0.068	0.276	.78	
JS on University Prepared Me (27.1)	0.004	0.061	0.072	.94	

JS on Casework Skills (28)	0.022	0.091	0.248	.80
JS on Disabled/Special Needs Skills (36)	0.060	0.071	0.850	.40
JS on Supervisor Relations Parcel	0.009	0.079	0.119	.91
JS on Role Overload Parcel	0.029	0.104	0.282	.78
JS on Rural*BSW	0.132	0.232	0.570	.57

Note. JS = job satisfaction. * = $p \leq .05$. z statistic calculated as difference in slopes divided by the standard error of the difference in slopes. Only modification indices greater than 3.841 are shown, since this value corresponds to statistical significance ($p < .05$).

Table 8 Final Model Results

Parameter	Non-Title IV-E				Title IV-E				Group Differences			
	Estimate (SE)	95% CI	z	Sig.	Estimate (SE)	95% CI	z	Sig.	Estimate (SE)	95% CI	z	Sig.
ITS Intercept	-0.34 (0.20)	-0.73, 0.04	-1.74	.08	-0.95 (0.27)	-1.47, -0.42	-3.55	<.001	-0.6 (0.24)	-1.07, -0.14	-2.54	.01
ITS R ²	.42 (.03)	.37, .48	15.63	<.001	.47 (.04)	0.40, 0.54	13.03	<.001		n.s.		
ITS regressed on:												
Job Satisfaction (22.3)	0.34 (0.05)	0.25, 0.44	7.17	<.001		Same as Non-IVE				n.s.		
Employment Dur.	0.03 (0.01)	0.01, 0.04	4.26	<.001	0.03 (0.01)	0.02, 0.05	3.62	<.001	0.01 (0.01)	-0.01, 0.03	0.89	.37
Years Prior Social Service Employment	0.00 (0.01)	-0.01, 0.01	0.35	.73	0.02 (0.01)	0.00, 0.04	2.29	.02	0.02 (0.01)	0, 0.04	1.80	.07
Years Prior Non-Social Service Employment	0.01 (0.01)	0.00, 0.02	1.62	.11		Same as Non-IVE				n.s.		
BSW (1=Yes)	0.12 (0.07)	-0.01, 0.25	1.80	.07		Same as Non-IVE				n.s.		
MSW (1=Yes)	-0.50 (0.14)	-0.77, -0.22	-3.55	<.001	-0.29 (0.11)	-0.52, -0.07	-2.58	.01	0.21 (0.18)	-0.15, 0.56	1.14	.25
Professional Dev. (22.2)	0.01 (0.04)	-0.06, 0.09	0.34	.73		Same as Non-IVE				n.s.		
Coworker Respect (25.3)	-0.11 (0.05)	-0.21, -0.02	-2.27	.02		Same as Non-IVE				n.s.		
Work Unit Cohesive (25.4)	0.06 (0.04)	-0.01, 0.14	1.67	.10		Same as Non-IVE				n.s.		
Supervisor Relations Parcel	0.06 (0.04)	-0.03, 0.14	1.26	.21		Same as Non-IVE				n.s.		
Role Overload Parcel	0.02 (0.06)	-0.09, 0.13	0.37	.71		Same as Non-IVE				n.s.		
University Prepared Me (27.1)	0.06 (0.03)	0.01, 0.12	2.16	.03		Same as Non-IVE				n.s.		
Casework Skills (28)	0.02 (0.04)	-0.06, 0.11	0.54	.59	0.27 (0.10)	0.08, 0.46	2.78	.01	0.25 (0.11)	0.04, 0.45	2.34	.02
Disabled/Special Needs Skills (36)	0.04 (0.04)	-0.05, 0.12	0.85	.39	0.17 (0.07)	0.04, 0.31	2.47	.01	0.14 (0.08)	-0.02, 0.3	1.68	.09
Salary Satisfaction (22.1)	0.08 (0.03)	0.03, 0.14	2.92	<.001		Same as Non-IVE				n.s.		
Position (1=Mgr. or Supv.)	0.07 (0.06)	-0.06, 0.19	1.07	.28		Same as Non-IVE				n.s.		
Rural (1=Yes)	0.22 (0.07)	0.07, 0.36	2.97	<.001	0.04 (0.12)	-0.19, 0.27	0.31	.75	-0.18 (0.14)	-0.45, 0.09	-1.31	.19
Non-White (1=Yes)	-0.18 (0.06)	-0.3, -0.06	-2.93	<.001		Same as Non-IVE				n.s.		
Age	0.03 (0.01)	0.02, 0.05	6.17	<.001		Same as Non-IVE				n.s.		
Age*Rural	-0.01 (0.01)	-0.02, 0.00	-1.89	.06		Same as Non-IVE				n.s.		
Gender (1=Male)	0.09 (0.10)	-0.11, 0.28	0.89	.37	-0.32 (0.17)	-0.64, 0.01	-1.92	.06	-0.4 (0.19)	-0.78, -0.03	-2.12	.03

Parameter	Non-Title IV-E				Title IV-E				Group Differences			
	Estimate (SE)	95% CI	z	Sig.	Estimate (SE)	95% CI	z	Sig.	Estimate (SE)	95% CI	z	Sig.
Job Satisfaction Intercept	0.92 (0.14)	0.65, 1.19	6.60	<.001	0.87 (0.15)	0.57, 1.17	5.64	<.001	-0.05 (0.06)	-0.18, 0.07	-0.86	.39
Job Satisfaction R2	.46 (.03)	.41, .52	15.91	<.001	.41 (.04)	.34, .49	11.04	<.001	n.s.			
Job Satisfaction regressed on:												
Employment Dur.	0.01 (0.01)	0.00, 0.02	1.68	.09								
Years Prior Social Service Employment	0.00 (0.00)	0.00, 0.01	0.95	.34								
Years Prior Non-Social Service Employment	-0.01 (0.01)	-0.02, 0.00	-1.18	.24								
BSW (1=Yes)	0.04 (0.07)	-0.09, 0.17	0.60	.55								
BSW*Rural	0.25 (0.11)	0.04, 0.46	2.37	.02								
MSW (1=Yes)	-0.07 (0.08)	-0.21, 0.08	-0.90	.37								
Professional Dev. (22.2)	0.33 (0.04)	0.26, 0.40	9.45	<.001								
Coworker Respect (25.3)	-0.09 (0.04)	-0.17, -0.01	-2.17	.03								
Work Unit Cohesive (25.4)	0.09 (0.04)	0.02, 0.16	2.51	.01								
Supervisor Relations Parcel	0.15 (0.04)	0.07, 0.22	3.78	<.001								
Role Overload Parcel	0.25 (0.05)	0.16, 0.35	5.17	<.001	Same as Non-IVE							
University Prepared Me (27.1)	0.04 (0.03)	-0.01, 0.09	1.45	.15								
Casework Skills (28)	-0.04 (0.03)	-0.10, 0.02	-1.26	.21								
Disabled/Special Needs Skills (36)	0.09 (0.03)	0.03, 0.15	2.93	<.001								
Salary Satisfaction (22.1)	0.13 (0.02)	0.09, 0.17	5.93	<.001								
Position (1=Mgr. or Supv.)	0.07 (0.05)	-0.03, 0.17	1.38	.17								
Rural (1=Yes)	-0.01 (0.06)	-0.12, 0.10	-0.12	.91								
Non-White (1=Yes)	-0.10 (0.05)	-0.19, 0.00	-2.04	.04								
Age	0.01 (0.01)	0.00, 0.01	1.13	.26								
Gender (1=Male)	-0.06 (0.07)	-0.19, 0.07	-0.97	.34								

Note. SE = standard error. CI = confidence interval. n.s. = non-significant ($p > .05$). z = Estimate/SE.

Table 9 Results of Significance Tests of Mediated Paths

	Non-Title IV-E				Title IV-E			
	Estimate (SE)	95% CI	z	Sig.	Estimate (SE)	95% CI	z	Sig.
Employment Dur. → JS → ITS								
Total	0.03 (0.01)	0.02, 0.04	4.57	<.001	0.04 (0.01)	0.02, 0.06	3.87	<.001
Indirect	0.00 (0.00)	0.00, 0.01	1.62	.11	Same as Non-IVE			
Years Prior Social Service Employment → JS → ITS								
Total	0.00 (0.01)	-0.01, 0.01	0.58	.56	0.02 (0.01)	0.00, 0.04	2.49	.01
Indirect	0.00 (0.00)	0.00, 0.00	0.94	.35	Same as Non-IVE			
Years Prior Non-Social Service Employment → JS → ITS								
Total	0.01 (0.01)	0.00, 0.02	1.27	.21	Same as Non-IVE			
Indirect	0.00 (0.00)	-0.01, 0.00	-1.16	.25	Same as Non-IVE			
BSW (1=Yes) → JS → ITS								
Total	0.13 (0.07)	0.00, 0.27	1.91	.06	Same as Non-IVE			
Indirect	0.01 (0.02)	-0.03, 0.06	0.60	.55	Same as Non-IVE			
MSW (1=Yes) → JS → ITS								
Total	-0.52 (0.14)	-0.80, -0.24	-3.61	<.001	-0.32 (0.12)	-0.55, -0.09	-2.70	.01
Indirect	-0.02 (0.03)	-0.07, 0.03	-0.89	.37	Same as Non-IVE			
Professional Dev. (22.2) → JS → ITS								
Total	0.13 (0.04)	0.05, 0.20	3.20	<.001	Same as Non-IVE			
Indirect	0.11 (0.02)	0.07, 0.15	5.67	<.001	Same as Non-IVE			
Coworker Respect (25.3) → JS → ITS								
Total	-0.14 (0.05)	-0.24, -0.04	-2.75	.01	Same as Non-IVE			
Indirect	-0.03 (0.02)	-0.06, 0.00	-2.03	.04	Same as Non-IVE			
Work Unit Cohesive (25.4) → JS → ITS								
Total	0.09 (0.04)	0.02, 0.17	2.43	.02	Same as Non-IVE			
Indirect	0.03 (0.01)	0.00, 0.06	2.28	.02	Same as Non-IVE			
Supervisor Relations Parcel → JS → ITS								
Total	0.11 (0.04)	0.02, 0.19	2.44	.02	Same as Non-IVE			
Indirect	0.05 (0.02)	0.02, 0.08	3.43	<.001	Same as Non-IVE			
Role Overload Parcel → JS → ITS								
Total	0.11 (0.06)	0.00, 0.22	1.91	.06	Same as Non-IVE			
Indirect	0.09 (0.02)	0.05, 0.13	4.23	<.001	Same as Non-IVE			
University Prepared Me (27.1) → JS → ITS								
Total	0.08 (0.03)	0.02, 0.14	2.52	.01	Same as Non-IVE			
Indirect	0.01 (0.01)	-0.01, 0.03	1.45	.15	Same as Non-IVE			
Casework Skills (28) → JS → ITS								
Total	0.01 (0.05)	-0.08, 0.10	0.21	.83	0.26 (0.10)	0.06, 0.45	2.62	.01
Indirect	-0.01 (0.01)	-0.04, 0.01	-1.23	.22	Same as Non-IVE			
Disabled/Special Needs Skills (36) → JS → ITS								
Total	0.07 (0.05)	-0.02, 0.16	1.50	.13	0.21 (0.07)	0.07, 0.34	2.91	<.001
Indirect	0.03 (0.01)	0.01, 0.05	2.69	.01	Same as Non-IVE			
Salary Satisfaction (22.1) → JS → ITS								
Total	0.12 (0.03)	0.07, 0.18	4.46	<.001	Same as Non-IVE			
Indirect	0.04 (0.01)	0.03, 0.06	4.66	<.001	Same as Non-IVE			
Position (1=Mgr. or Supv.) → JS → ITS								
Total	0.09 (0.07)	-0.04, 0.22	1.41	.16	Same as Non-IVE			
Indirect	0.02 (0.02)	-0.01, 0.06	1.37	.17	Same as Non-IVE			
Rural (1=Yes) → JS → ITS								
Total	0.22 (0.08)	0.07, 0.37	2.81	.01	0.04 (0.12)	-0.20, 0.27	0.29	.77
Indirect	0.00 (0.02)	-0.04, 0.04	-0.12	.91	Same as Non-IVE			
Non-White (1=Yes) → JS → ITS								
Total	-0.21 (0.06)	-0.33, -0.09	-3.35	<.001	Same as Non-IVE			
Indirect	-0.03 (0.02)	-0.07, 0.00	-1.91	.06	Same as Non-IVE			
Age → JS → ITS								
Total	0.04 (0.01)	0.02, 0.05	6.08	<.001	Same as Non-IVE			
Indirect	0.00 (0.00)	0.00, 0.01	1.11	.27	Same as Non-IVE			
Gender (1=Male) → JS → ITS								
Total	0.07 (0.10)	-0.13, 0.26	0.66	.51	-0.34 (0.17)	-0.66, -0.01	-2.05	.04
Indirect	-0.02 (0.02)	-0.07, 0.02	-0.96	.34	Same as Non-IVE			

Note. SE = standard error. CI = confidence interval. z = Estimate/SE.

Table 10a Results of Post-Hoc Power Analysis: Regression Parameters

	Non-Title IV-E								Title IV-E							
	Pop. Parameter	Avg. Parameter Est.	Parameter Bias	Std. Dev.	Avg. Std. Error	Std. Error Bias	95% Coverage	% Sig.	Pop. Parameter	Avg. Parameter Est.	Parameter Bias	Std. Dev.	Avg. Std. Error	Std. Error Bias	95% Coverage	% Sig.
ITS regressed on:																
Age	0.034	0.034	0.00%	0.002	0.002	-4.17%	0.931	1.000								
Position (1=Mgr. or Supv.)	0.068	0.067	-1.47%	0.051	0.050	-1.18%	0.937	0.256								
Rural (1=Yes)	0.218	0.219	0.32%	0.057	0.058	2.82%	0.953	0.968	0.037	0.042	13.51%	0.114	0.099	-13.29%	0.920	0.114
Gender (1=Male)	0.087	0.088	0.57%	0.074	0.076	3.26%	0.956	0.209	-0.316	-0.317	0.35%	0.152	0.130	-14.91%	0.909	0.652
Non-White (1=Yes)	-0.178	-0.177	-0.84%	0.047	0.049	2.32%	0.957	0.957								
Employment Dur.	0.026	0.026	-0.38%	0.004	0.004	5.56%	0.968	1.000	0.034	0.034	1.18%	0.008	0.007	-13.10%	0.918	0.987
BSW (1=Yes)	0.119	0.118	-1.09%	0.065	0.062	-4.33%	0.945	0.480								
MSW (1=Yes)	-0.498	-0.499	0.18%	0.101	0.103	1.59%	0.945	0.998	-0.293	-0.296	0.99%	0.208	0.177	-15.09%	0.900	0.435
Years Prior Social Service Employment	0.002	0.002	-5.00%	0.003	0.004	2.94%	0.959	0.073	0.020	0.020	2.00%	0.008	0.007	-14.81%	0.902	0.804
Years Prior Non-Social Service Employment	0.010	0.010	-1.00%	0.003	0.003	0.00%	0.952	0.920								
Salary Satisfaction (22.1)	0.080	0.080	0.13%	0.022	0.022	-0.91%	0.953	0.957								
Professional Dev. (22.2)	0.013	0.012	-6.92%	0.026	0.026	1.94%	0.960	0.068								
Job Satisfaction (22.3)	0.344	0.344	0.06%	0.029	0.029	0.34%	0.943	1.000								
Coworker Respect (25.3)	-0.110	-0.110	-0.27%	0.036	0.034	-5.34%	0.939	0.896								
Work Unit Cohesive (25.4)	0.062	0.061	-0.97%	0.024	0.025	2.06%	0.952	0.716								
University Prepared Me (27.1)	0.063	0.064	0.95%	0.021	0.021	0.00%	0.946	0.856								
Casework Skills (28)	0.023	0.023	-2.17%	0.034	0.035	1.47%	0.950	0.099	0.269	0.270	0.22%	0.087	0.075	-13.41%	0.902	0.914
Disabled/Special Needs Skills (36)	0.037	0.037	0.27%	0.032	0.034	5.99%	0.962	0.187	0.174	0.170	-2.24%	0.069	0.059	-14.45%	0.909	0.778
Supervisor Relations Parcel	0.055	0.055	-0.36%	0.029	0.028	-3.79%	0.949	0.509								
Role Overload Parcel	0.021	0.022	2.38%	0.031	0.032	1.60%	0.958	0.098								
Job Satisfaction regressed on:																
Age	0.005	0.005	4.00%	0.003	0.003	-3.85%	0.942	0.540								
Position (1=Mgr. or Supv.)	0.071	0.071	0.28%	0.057	0.056	-1.94%	0.944	0.277								
Rural (1=Yes)	-0.007	-0.006	-10.00%	0.057	0.055	-3.15%	0.945	0.057								
Gender (1=Male)	-0.064	-0.064	-0.47%	0.073	0.072	-1.50%	0.943	0.153								
Non-White (1=Yes)	-0.095	-0.095	0.11%	0.054	0.053	-1.29%	0.942	0.445								
Employment Dur.	0.008	0.008	0.00%	0.004	0.004	2.78%	0.958	0.604								
BSW (1=Yes)	0.040	0.040	0.75%	0.069	0.068	-1.59%	0.943	0.091								
MSW (1=Yes)	-0.067	-0.068	1.19%	0.100	0.097	-2.41%	0.943	0.107								
Years Prior Social Service Employment	0.004	0.004	0.00%	0.003	0.004	2.94%	0.947	0.212								
Years Prior Non-Social Service Employment	-0.006	-0.006	-1.67%	0.003	0.003	-5.88%	0.934	0.474								
Salary Satisfaction (22.1)	0.128	0.128	-0.08%	0.024	0.024	-2.07%	0.945	0.999								
Professional Dev. (22.2)	0.329	0.330	0.27%	0.028	0.027	-3.93%	0.937	1.000								
Coworker Respect (25.3)	-0.087	-0.087	0.11%	0.037	0.037	-0.27%	0.957	0.636								
Work Unit Cohesive (25.4)	0.089	0.089	-0.34%	0.027	0.027	1.50%	0.952	0.915								
University Prepared Me (27.1)	0.040	0.040	1.00%	0.023	0.023	0.00%	0.953	0.422								
Casework Skills (28)	-0.040	-0.041	2.25%	0.036	0.035	-4.43%	0.935	0.230								
Disabled/Special Needs Skills (36)	0.089	0.088	-1.01%	0.031	0.032	4.92%	0.954	0.795								
Supervisor Relations Parcel	0.147	0.145	-1.09%	0.032	0.030	-4.11%	0.941	0.998								
Role Overload Parcel	0.252	0.252	-0.08%	0.035	0.034	-2.02%	0.949	1.000								
Intercepts																
ITS	-0.342	-0.340	-0.61%	0.139	0.142	2.16%	0.948	0.691	-0.945	-0.941	-0.48%	0.251	0.220	-12.23%	0.908	0.981

Job Satisfaction	0.920	0.920	0.00%	0.148	0.145	-1.76%	0.944	1.000	0.866	0.869	0.30%	0.146	0.148	1.30%	0.958	1.000
Residual Variances																
ITS	0.737	0.539	-26.89%	0.025	0.025	-3.16%	0.000	1.000								
Job Satisfaction	0.493	0.659	33.65%	0.031	0.030	-4.17%	0.000	1.000								

Same as Non-IVE

Note. Numbers in bold indicate results that exceed the following recommended (Muthén, 2002) limits: parameter bias exceeding $\pm 10\%$, standard error bias exceeding $\pm 5\%$, coverage not within 0.91 and 0.98, power less than 0.80.

Table 10b Results of Post-Hoc Power Analysis: Group Differences and Indirect Effects

	Pop. Parameter	Avg. Parameter Est.	Parameter Bias	Std. Dev.	Avg. Std. Error	Std. Error Bias	95% Coverage	% Sig.
Δ Rural	-0.181	-0.177	-2.32%	0.125	0.115	-7.99%	0.927	0.356
Δ Gender	-0.403	-0.405	0.40%	0.171	0.150	-11.95%	0.917	0.738
Δ Emp. Duration	0.008	0.009	6.25%	0.009	0.008	-11.83%	0.918	0.213
Δ MSW	0.205	0.203	-0.98%	0.230	0.205	-10.89%	0.917	0.201
Δ Yrs. Prior Soc. Svc. Emp.	0.018	0.019	2.78%	0.009	0.008	-11.36%	0.912	0.643
Δ Casework Skills (28)	0.246	0.247	0.45%	0.094	0.083	-11.86%	0.911	0.822
Δ Disabled Skills (36)	0.137	0.133	-2.92%	0.075	0.067	-10.49%	0.927	0.494
Employment Dur. → JS → ITS	0.003	0.003	-6.67%	0.001	0.001	0.00%	0.953	0.597
Years Prior Social Service Employment → JS → ITS	0.001	0.001	40.00%	0.001	0.001	0.00%	0.946	0.202
Years Prior Non-Social Service Employment → JS → ITS	-0.002	-0.002	0.00%	0.001	0.001	-8.33%	0.939	0.463
BSW (1=Yes) → JS → ITS	0.014	0.014	-0.71%	0.024	0.024	-2.08%	0.943	0.090
MSW (1=Yes) → JS → ITS	-0.023	-0.023	1.30%	0.035	0.034	-2.60%	0.948	0.101
Professional Dev. (22.2) → JS → ITS	0.113	0.114	0.53%	0.014	0.013	-2.19%	0.946	1.000
Coworker Respect (25.3) → JS → ITS	-0.030	-0.030	0.00%	0.013	0.013	0.78%	0.943	0.625
Work Unit Cohesive (25.4) → JS → ITS	0.031	0.031	-1.29%	0.010	0.010	-1.02%	0.946	0.912
Supervisor Relations Parcel → JS → ITS	0.051	0.050	-1.96%	0.012	0.011	-2.59%	0.940	0.997
Role Overload Parcel → JS → ITS	0.087	0.087	-0.34%	0.015	0.014	-4.14%	0.939	1.000
University Prepared Me (27.1) → JS → ITS	0.014	0.014	-0.71%	0.008	0.008	0.00%	0.955	0.408
Casework Skills (28) → JS → ITS	-0.014	-0.014	0.00%	0.013	0.012	-4.00%	0.938	0.222
Disabled/Special Needs Skills (36) → JS → ITS	0.031	0.030	-2.26%	0.011	0.011	5.56%	0.957	0.786
Salary Satisfaction (22.1) → JS → ITS	0.044	0.044	0.00%	0.009	0.009	-1.10%	0.938	0.999
Position (1=Mgr. or Supv.) → JS → ITS	0.024	0.025	2.08%	0.020	0.019	-1.53%	0.946	0.271
Rural (1=Yes) → JS → ITS	-0.002	-0.002	5.00%	0.020	0.019	-3.03%	0.946	0.051
Non-White (1=Yes) → JS → ITS	-0.033	-0.033	-0.91%	0.019	0.019	-1.59%	0.949	0.437
Age → JS → ITS	0.002	0.002	-10.00%	0.001	0.001	0.00%	0.929	0.527
Gender (1=Male) → JS → ITS	-0.022	-0.022	-0.45%	0.026	0.025	-1.96%	0.947	0.144

Note. Numbers in bold indicate results that exceed the following recommended (Muthén, 2002) limits: parameter bias exceeding $\pm 10\%$, standard error bias exceeding $\pm 5\%$, coverage not within 0.91 and 0.98, power less than 0.80.

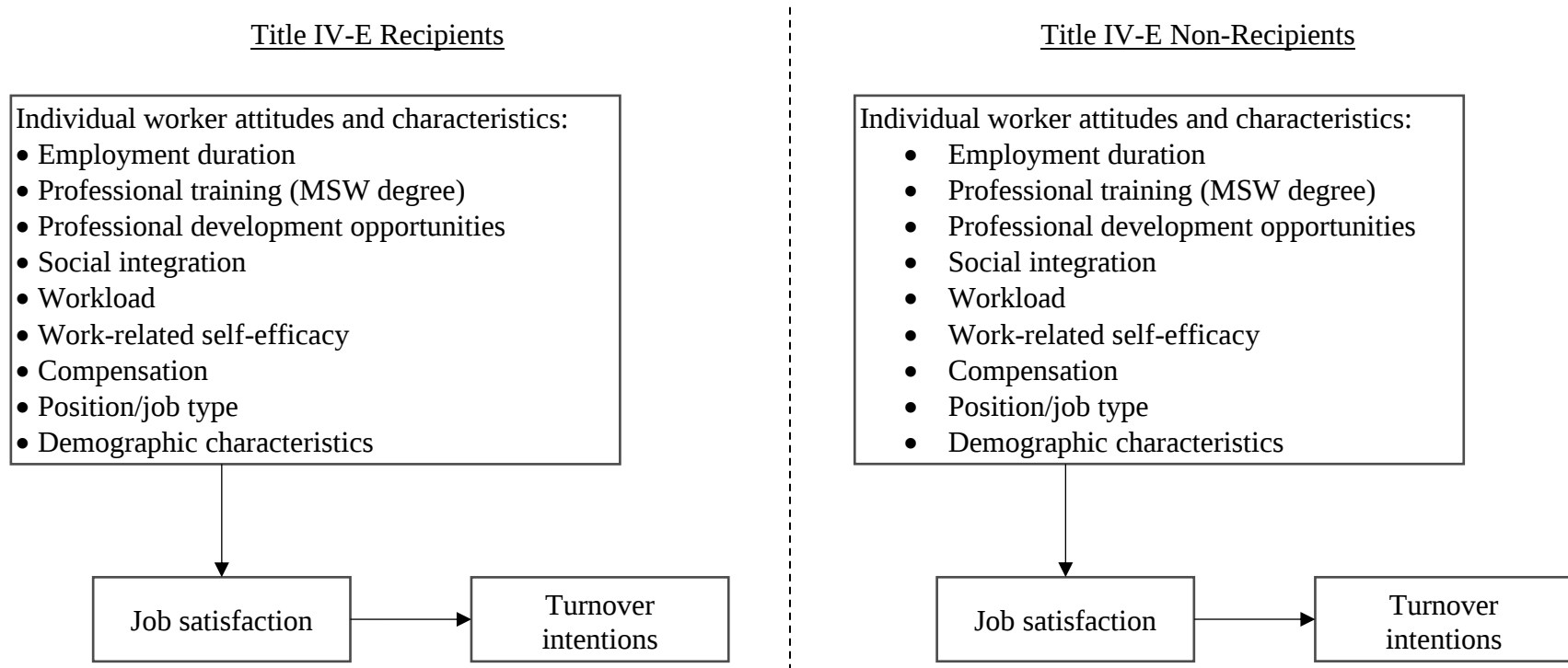
Figures

Figure 1. Adapted from Landsman (2001). Individual worker characteristics influence turnover intentions indirectly via job satisfaction. Model parameters to be estimated separately for each group and then statistically compared to check for moderation of Title IV-E status.

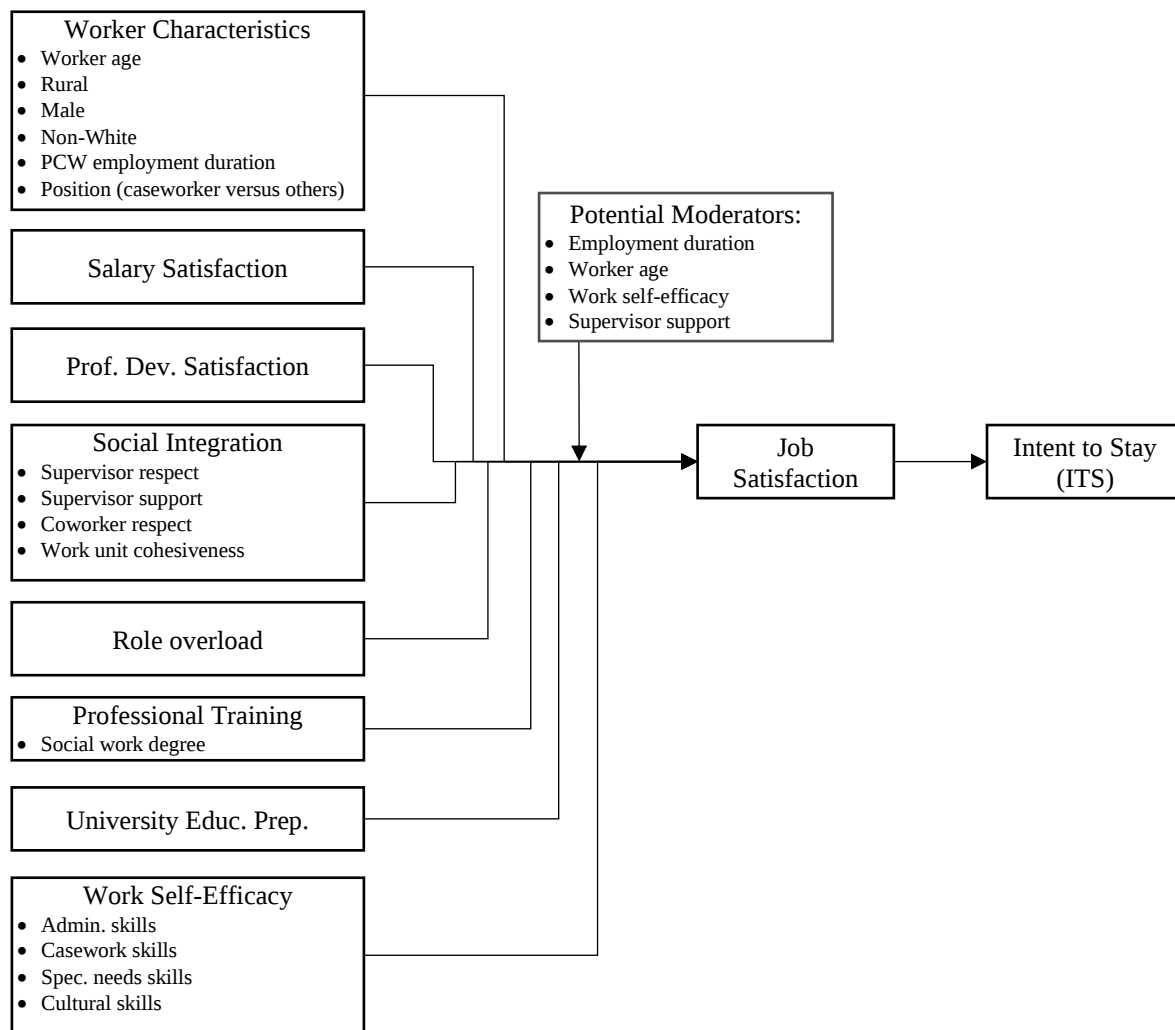


Figure 2. Detailed view of conceptual model presented in Figure 1. Rectangles indicate manifest (observed) variables; the hexagon indicates a composite variable. All parameters estimated separately within each group (Title IV-E recipients versus non-recipients).

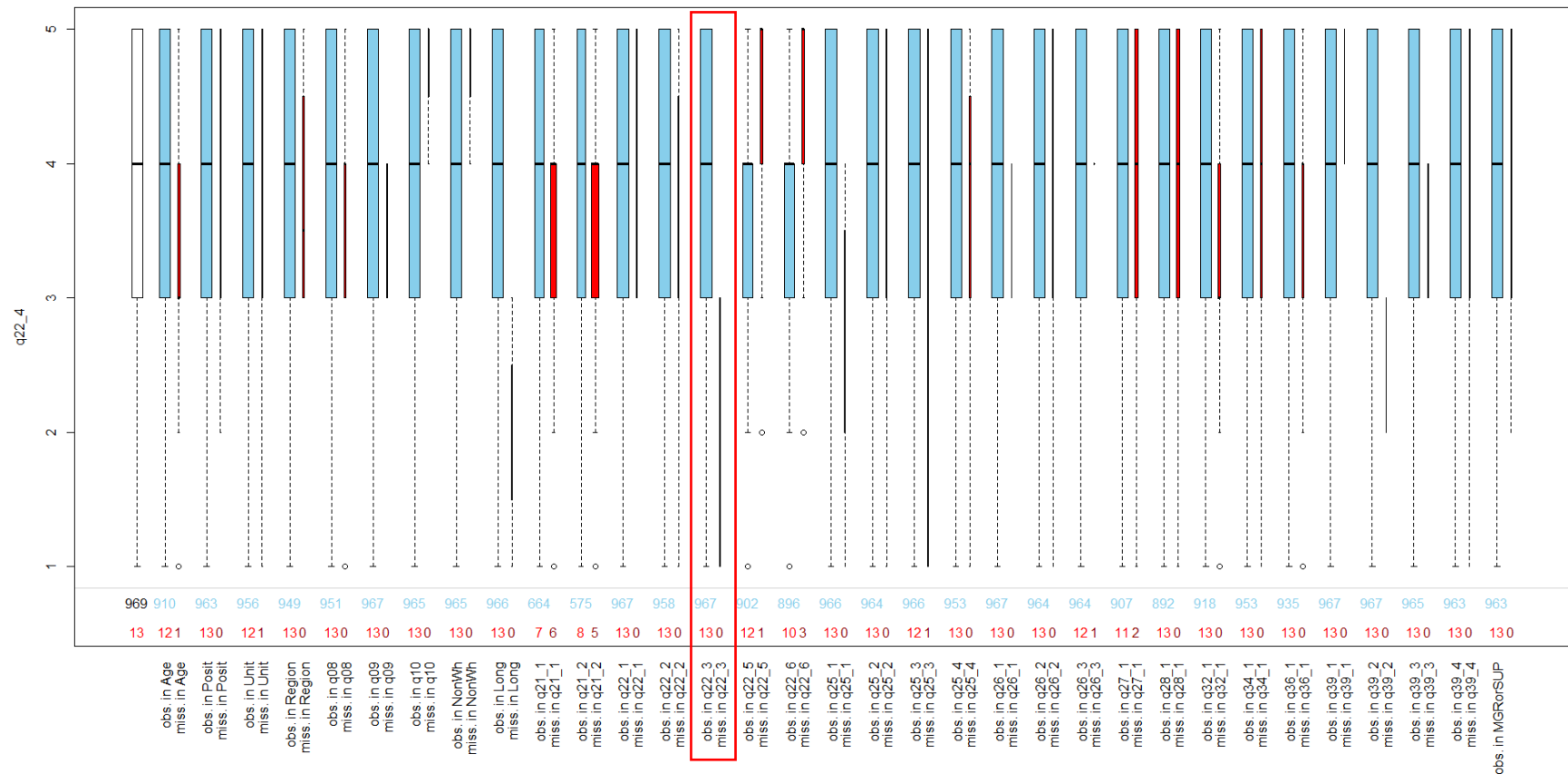


Figure 3. Parallel boxplots with information about missing values, generated using the **VIM** package for R (Templ & Filzmoser, 2008). Boxplots shown within the red rectangle indicate item 22.4 (plan to retire from agency, plotted on the y-axis) tends to be lower when data for item 22.3 (job satisfaction) is missing. This indicates MAR missing data: missingness on one DV is related to another DV. In this case, missingness on job satisfaction is related to intent to retire from the agency.

Appendix A: Survey Instrument Cover Letter

Dear Participants:

I am Professor Patrick Leung from the University of Houston Graduate College of Social Work. I chair the Texas Roundtable Title IV-E Evaluation Committee and I would like to request your participation in a research project entitled 'The Impact of Title IV-E Training on CPS Caseworkers and Case Outcomes'. We are conducting a survey to assess the level of worker satisfaction with child protection. The purpose of this study is to collect information from all employees of DFPS.

Data will be gathered using an evaluation survey developed by the Title IV-E Evaluation Committee. Participants will be asked to access and complete the survey by using a link to SurveyMonkey.com. You will be able to stop and go back at a later time to complete the survey. However, once the survey has been submitted, no changes can be made and participants may not complete another survey. Participants will be asked to provide the "Employee ID", "Name" and "Person ID" based on the Impact System. After you complete the survey, the investigator will merge your responses from the survey with the child case outcomes files (from 2004 to 2005) provided by the DFPS administrator.

The information obtained from the survey and the case outcomes will be kept strictly confidential. Only a summary of the data will be reported. Your Employee ID, Name and Person ID in association with the case outcome or your personal identity will not be reported in any part of the report. After the files are merged, your Employee ID, Name and Person ID will be erased and you will not be identified in the data base. The final report will only identify the characteristics of case workers in an aggregate form, including demographic data, previous professional experience, and job satisfaction. We estimate that completion of this survey will take approximately 15 minutes.

We do not foresee that you should experience any risks as a result of your participation in this research project. Nevertheless, some of the material may be regarded as sensitive and you are free to discontinue participation at any time. In addition, we do not foresee that you will receive any direct, personal benefit as a result of your participation in this project; however, your participation will allow researchers to better understand the impact of Title IV-E training on case outcomes. Such information can contribute to knowledge about working with children.

You have several choices regarding non-participation of this project: 1) you may decide not to participate at all; 2) you may decide not to answer some of the questions, or 3) you may decide to terminate your participation even after you have begun. Any of these choices is an option and you will not suffer any penalty. If you choose to fill out any portion of the survey, you hereby consent to participate in this study.

The data collected from this research project will be used for education, research, and publication purposes. The data gathered from this research project will not be identified with you personally. Please submit your completed survey via the link at SurveyMonkey.com. Any questions about this research or any related problems may be directed to the Principal Investigator, Dr. Patrick Leung, Professor in the Graduate College of Social Work, at [redacted].

ANY QUESTIONS REGARDING YOUR RIGHTS AS A RESEARCH SUBJECT MAY BE
ADDRESSED TO THE UNIVERSITY OF HOUSTON COMMITTEE FOR THE

PROTECTION OF HUMAN SUBJECTS (713-743-9204). ALL RESEARCH PROJECTS THAT ARE CARRIED OUT BY INVESTIGATORS AT THE UNIVERSITY OF HOUSTON ARE GOVERNED BY THE REQUIREMENTS OF THE UNIVERSITY AND THE FEDERAL GOVERNMENT.

Appendix B: Scale Items

- 22.1 I am satisfied with my current salary. (salary satisfaction)
- 22.2 I am currently satisfied with my professional development. (professional development satisfaction)
- 22.3 I am satisfied with my current job. (job satisfaction)
- 22.4 I plan to retire from [this agency]. (intent to stay)
- 22.5 I intend to leave [this agency] within in the next twelve months. (intent to stay; reverse scored)
- 22.6 I have future plans to get a job outside [this agency]. (intent to stay; reverse scored)
- 25.1 My direct supervisor respects my knowledge, skills, and experience. (supervisor respect)
- 25.2 My supervisor provides me with support so that I can be an effective worker. (supervisor support)
- 25.3 My co-worker(s) respect(s) my knowledge, skills, and experience. (coworker respect)
- 25.4 My work unit is cohesive. (work unit cohesiveness)
- 26.2 I feel that I can accomplish a satisfactory amount of work during an ordinary day. (role overload)
- 26.3 I am able to satisfy the multiple demands of my job with the current resources available. (role overload)
- 27.1 My university education prepared me to handle my job. (work self-efficacy)
- 28. Please rate the item below by indicating the number that best describes your skill level:
Casework Skills (work self-efficacy)
- 32. Please rate the item below by indicating the number that best describes your skill level:
Administrative Skills (work self-efficacy)
- 34. Please rate the item below by indicating the number that best describes your skill level:
Skills working with culturally diverse populations (work self-efficacy)
- 36. Please rate the item below by indicating the number that best describes your skill level:
Skills working with persons with disabilities and/or special needs (work self-efficacy)

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