# INDIVIDUALS WITH DISABILITIES IN SELF-EMPLOYMENT THROUGH VOCATIONAL REHABILITATION AGENCIES ACROSS THE UNITED STATES

by

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DISSERTATION ABSTRACT

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Title: Individuals with Disabilities in Self-Employment through Vocational Rehabilitation Agencies across the United States

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Despite numerous legislative and programmatic efforts, individuals with disabilities continue to experience greater difficulties gaining employment and poorer outcomes of employment than individuals without disabilities. These disparities negatively impact society. My review of the U.S. empirical research literature suggests, however, that self-employment could improve employment opportunities and outcomes for individuals with disabilities, and their success is most influenced by individual characteristics, level of supports, and accountability systems.

In this dissertation study, I used a nonexperimental research design to investigate six research questions with Hierarchical Linear Modeling (HLM) and Structural Equation Modeling (SEM) statistical analyses. Extant data on more than a million clients of vocational rehabilitation (VR) agencies from the 50 states and District of Columbia for fiscal years 2003 to 2007 were obtained from the Rehabilitation Services Administration.

Results of the HLM analysis indicated that among the significant ($p<.001$) predictors of self-employment closure across the fiscal years, ethnicity had the strongest

effect. The initial SEM analysis produced an inadmissible solution; the respecified model of individual characteristics, level of supports, and accountability systems produced a reasonable model fit in each fiscal year. The model invariance testing across the four U.S. Census Regions indicated a reasonable fit in each fiscal year when model parameters were freely estimated for each region, but very poor fit and significant differences were indicated when some parameters were fixed to be equal across the regions.

The major limitations of this dissertation study are model misspecification in HLM and SEM and the small number of RSA fiscal years that were analyzed; causal inferences cannot be made. The primary implication of this study for researchers is using the results of the statistical analyses to develop and test theories about self-employment of individuals with disabilities through VR. The primary implication for VR is using the results to make decisions about services and agency policies. Recommendations for further research include (a) using Laplace estimation in HLM, (b) analyzing other HLM random effects and predictors, (c) testing a SEM model of different indicators and factor structure with Bayesian estimation, and (d) conducting empirical longitudinal studies given the complex developmental processes of self-employment.

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I dedicate this dissertation to my father Michael, my mother Karen, and my sister Kelly.
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# CHAPTER I

# INTRODUCTION

Work is an indispensable human activity. Adam Smith explains in *The Wealth of Nations* that as societies have developed, labor and capital have combined to create markets and transform work into employment opportunities (Smith, 2000). Not only has employment become necessary and prevalent, but an indicator of social status; and a rite of passage or transition to adulthood for some (Rice & Dolgin, 2005). The importance of employment can also be observed in the frequency with which government agencies and nongovernment organizations collect and use employment data.

Over the last four decades, the issue of employment in the United States has gained salience among individuals with disabilities. In particular, laws have raised the issue's visibility and expanded employment opportunities, including self-employment. The purpose of this dissertation study is to analyze self-employment of individuals with disabilities through vocational-rehabilitation agencies across the country. Meanwhile, research has studied the issue of employment and its conceptualization, focusing on adults with disabilities and on post-school employment preparation of secondary students with disabilities. That research also has continued to evolve over several decades.

## Evolution of Employment for Individuals with Disabilities in the U.S.

In the 1970s, employment of adults with disabilities was impacted by the twin ideas of normalization and deinstitutionalization. The philosophy of normalization (Nirje, 1969; Wolfensberger, 1972) for human services meant ". . . the delivery of services in environs and under contingencies that are as culturally normal as possible" (Rusch & Hughes, 1990, p.6). Deinstitutionalization of those with severe disabilities resulted in the growth of employment programs commonly referred to as sheltered workshops, which operated as nonintegrated settings where individuals received paid training in preparation for competitive employment (Parent & Hill, 1990). Despite some successful programs from the late 1970s through the 1980s, however, significant improvement in outcomes did not occur, and substantial gaps were identified between research-based indicators of program quality and actual practices (Renzaglia & Everson, 1990). To this day, individuals who enter sheltered workshops largely remain there; they do not proceed to integrated competitive employment (Inge, Wehman, Revell, Erickson, Butterworth, & Gilmore, 2009). As an alternative approach, supported employment was developed in the mid-1970s to increase competitive-employment opportunities and later codified by the Developmental Disabilities Act of 1984 (P.L. 98-527), mandating competitive work, ongoing support, and integrated work settings (Rusch & Hughes, 1990).

In the early 1980s, the importance of in-school preparation of secondary students with disabilities for post-school employment was recognized by policymakers. Reacting to chronically poor employment outcomes of adults with disabilities, the Office of Special Education and Rehabilitative Services (OSERS) defined the federal role in the school-to-work "transition" of secondary students with disabilities in 1984 (National Council on Disability and the Social Security Administration, 2000). As its policy, OSERS identified employment as the ultimate goal of the transition process (Will, 1984). In a direct response, however, Halpern (1985) proposed an alternative perspective, identifying "community adjustment" as the ultimate goal, with employment, residential environment, and social and interpersonal networks serving as the three determinative factors for reaching that goal. During this time, research (e.g., Hasazi, Gordon, & Roe,

1985) had also become focused on examining the effects of in-school programs, services, and activities on students' post-school adult outcomes.

The landmark special-education law, *Education for All Handicapped Children Act* of 1974 amended a year later as the *Education for the Handicapped Act* (P.L. 94-142), was reauthorized and renamed in 1990 as the *Individuals with Disabilities Education Act* (P.L. 101-476). This reauthorized law further clarified the definition of transition, broadening its focus from employment to include other outcomes, such as post-secondary and continuing-adult education, independent living, community participation, and vocational training. Halpern (1993) posited that this revised and expanded definition implied that a new framework for understanding and evaluating transition processes and outcomes could be "quality of life," in which individual choice and social norms are to be reconciled across three outcome domains: (a) personal fulfillment, (b) physical and material well-being, and (c) performance of adult roles.

Throughout the 1990s, federal priority on improving transition outcomes resulted in numerous mandates, including the School-to-Work Opportunities Act of 1994 (P.L. 103-239), Workforce Investment Act of 1998 (P.L. 105-220), and Ticket to Work and Work Incentives Improvement Act of 1999 (P.L. 106-170). These legislative efforts also impacted research, which increasingly focused on specific quality of life, cross-domain transition issues of individual choice and self-determination in career development for adults with disabilities (e.g., Hartnett, Collins, & Tremblay, 2002; Izzo & Lamb, 2003), and of improving and tailoring services to meet individual needs through customized employment and One-Stop Centers (e.g., Citron, Brooks-Lane, Crandell, Brady, Cooper,

& Revell, 2008; Inge, 2006). Many of the research studies, though, also raised concerns and questions about the efficacy of the various legislative efforts.

**Employment Outcomes for Individuals with Disabilities**

Despite a number of federal initiatives, programs, and services, significant improvements in employment opportunities and outcomes have not occurred for adults with disabilities. For example, comparing results from the National Longitudinal Transition Study-1 and the National Longitudinal Transition Study-2, which were conducted over the last two decades respectively, Newman, Wagner, Cameto, Knokey, and Shaver (2010) found that the two cohorts of young adults with disabilities did not differ in employment status, hours worked per week, job duration, or average hourly wages. In a recent national survey by the U.S. Department of Labor, only 19.1% of companies reported employing individuals with disabilities and only 13.6% reported actively recruiting individuals with disabilities, with the public sector more likely to actively recruit and hire than the private sector (Domzal, Houtenville, & Sharma, 2008).

Across the U.S., chronic employment and income disparities are found between individuals with disabilities and individuals without disabilities. The U.S. Census Bureau (2008) reported that approximately 45.6% of individuals with a disability 21 to 64 years of age were employed with median monthly earnings of $1917; whereas 83.5% of individuals without a disability in that age group were employed with median monthly earnings of $2539. In addition, 27.1% of individuals with a severe disability and 12.0% with a nonsevere disability 25 to 64 years of age were categorized as “living in poverty”; whereas 9.1% of individuals without a disability in the same age group were categorized as such (http://www.census.gov/prod/2008pubs/p70-117.pdf). These outcomes affirm that individuals with disabilities remain at risk of social stigma, diminished self-esteem and self-determination, dependence on government aid, and other persistent challenges.

A growing body of information suggests self-employment can be a sustainable, viable answer for improving socioeconomic and employment outcomes of individuals with disabilities. According to the U.S. Department of Labor (2007), individuals with disabilities are "nearly twice as likely to be self-employed as the general population, 14.7 percent to 8 percent" (http://www.dol.gov/odep). This prevalence can be explained in part by the (a) shift in the U.S. economy from industrial manufacturing to a high-technology, information and services economy; and (b) philosophy and movement of consumer choice and self-determination in employment for individuals with disabilities (Colling & Arnold, 2007; Palmer, Schriner, Getch, & Main, 2000; Rizzo, 2002; Schriner & Neath, 1996; Seekins, 1992; Walls, Dowler, Cordingly, Orslene, & Greer, 2001). Others have surmised that self-employment is viable because it can be less stigmatizing than other employment options as it connects the "American Dream" of owning a business ". . . with the commitment of rehabilitation professionals, family members, friends and neighbors to assist people with disabilities in achieving typical lives" (Griffin & Hammis, 2008, p.2).

The two recessions that book-ended the last decade mark a continuing evolution of the globalized U.S. economy. As traditional wage and salary employment is being redefined, emerging markets could expand opportunities for self-employment. Economic changes also have been linked to technological advances that have included significant innovations such as digital-wireless communications and social networking media. These innovations have contributed to the growth and viability of internet commerce, which has the potential to ameliorate self-employment barriers related to disability. For example, an analysis of data on U.S. veterans with service-connected disabilities found that computer ownership correlated with a higher rate of self-employment (Open Blue Solutions, 2007).

**Prevalence of Self-Employment in the U.S.**

Self-employment is a distinct alternative to working for others. That choice or decision can involve an array of factors, circumstances, and reasons. One may seek a certain degree of financial independence and work autonomy, pursue product or service innovation or invention, or run a family business. In the United States, small business has generally been regarded as vital to its free-enterprise entrepreneurial system, economic strength, and global competitiveness (http://www.sba.gov/). Rates of self-employment, however, have decreased from approximately 18.5% in 1948, to 7.5% in 2003 (http: www.bls.gov/opub/ted/2004/aug/wk4/art02.htm). Much of this decrease is attributed to the (a) decline in agricultural self-employment, particularly, small independent farms (and increase in large corporate farms and agricultural productivity) and (b) change in classifications to separate unincorporated and incorporated self-employment categories, with the latter tallying individuals as “wage and salary employees of their own businesses” starting in 1967 (Hipple, 2004; also http://www.bls.gov/opub/ted/2004/aug/wk4/art02.htm). The self-employment rate of 7.5% in 2003 only represented individuals, ages 16 years and older, in *unincorporated* self-employment or 10,295,000 out of 137,735,000 in total employment. The 3.6% rate of *incorporated* self-employment represented 4,956,000 individuals (Hipple, 2004).

In addition to the 1967 classification change in self-employment, recent changes complicate direct historical comparisons across the incorporated and unincorporated, agricultural and nonagricultural industries. Changes were made to the 1994 U.S. Current

Population Survey and additional classification systems were adopted in 2003, including the 2000 Standard Occupational Classification and the 2002 North American Industry Classification System (Hipple, 2004). In 2003, numbering 9,344,000 out of 10,295,000 individuals in unincorporated self-employment were those in nonagricultural industries; while 4,810,000 out of 4,956,000 individuals in incorporated self-employment were also those in nonagricultural industries (Hipple, 2004).

In 2007, an estimated 856,000 individuals in self-employment, ages 16 years and older, were in unincorporated agriculture (http://www.bls.gov/cps/cpsaat12.pdf). Most individuals in self-employment, however, were still in unincorporated nonagricultural industries, an estimated 9,557,000 out of 146,047,000 in total employment (http://www.bls.gov/cps/cpsaat15.pdf). Among the 9,557,000 individuals, 62% or 5,920,000 were male, and 73% of males were between 35 and 64 years of age. Among nonagricultural industries in unincorporated self-employment, the largest was "professional and business services" for both women and men, followed by "education and health services" for women and "construction" for men (http://www.bls.gov/cps/cpsaat16.pdf).

**Vocational Rehabilitation Services in the U.S.**

The role of the U.S. federal government in the self-employment of individuals with disabilities commenced with the Rehabilitation Act of 1973, subsequently amended by the Workforce Investment Act of 1998 Title IV Rehabilitation Act Amendments. The purposes of the Act are ". . . (1) to empower individuals with disabilities to maximize employment, economic self-sufficiency, independence, and inclusion and integration into society . . . and (2) to ensure that the Federal Government plays a leadership role in promoting the employment of individuals with disabilities." Section 102(a)(1) outlines the Vocational Rehabilitation (VR) services eligibility criteria: “An individual is eligible for assistance under this title if the individual – (A) is an individual with a disability under section 7(20)(A); and (B) requires vocational rehabilitation services to prepare for, secure, retain, or regain employment.” Section 103 describes these services as “. . . any services described in an individualized plan for employment necessary to assist an individual with a disability in preparing for, securing, retaining, or regaining an employment outcome that is consistent with the strengths, resources, priorities, concerns, abilities, capabilities, interests, and informed choice of the individual.”

Individuals with disabilities can be referred for eligibility determination and subsequent services to their home state VR agency by a number of sources, including but not limited to educational institutions, medical personnel or institutions, welfare agency (state/local government), community rehabilitation programs, the Social Security Administration, and One-stop Employment/Training Centers. Individuals can also refer themselves to their state VR agency (Rehabilitation Services Administration, 2005).

Regarding self-employment, Section 7(11)(c) of the Act establishes it as an employment outcome: “The term ‘employment outcome’ means, with respect to an individual -- satisfying any other vocational outcome the Secretary may determine to be appropriate (including satisfying the vocational outcome of self- employment, telecommuting, or business ownership), in a manner consistent with this Act.” Section 103(a)(13) defines VR support and services, including “. . . technical assistance and other consultation services to conduct market analyses, develop business plans, and otherwise provide resources . . . to eligible individuals who are pursuing self-employment or telecommuting or establishing a small business operation as an employment outcome." Section 103(b)(1) defines other VR services for self-employment:

> In the case of any type of small business operated by individuals with significant disabilities the operation of which can be improved by management services and supervision provided by the designated State agency, the provision of such services and supervision, along or together with the acquisition by the State agency of vending facilities or other equipment and initial stocks and supplies.

While the VR process for self-employment of individuals with disabilities is not identical across states, an example of this process is outlined by the Oregon Vocational Rehabilitation Services (http://www.myworkweb.biz/self_employment_process.htm). A two-step process, in sequential order, is involved: (1) assessment and (2) development of an individualized plan for employment. The first step focuses on a client's potential in self-employment, examining his/her interests, aptitude, skills, and other factors, such as medical and psychological evaluations and observations and assessments of a client's initiative and enthusiasm. Also, the first step includes the (a) development of a business plan, (b) determining the viability of the business plan, and (c) application for financial assistance. The most important part of this step is the business plan, which can involve outside professional business consultants to provide technical expertise and assistance.

The second step in the VR self-employment case process is the development of an individualized plan for employment, which occurs after the VR counselor and client have agreed that self-employment as a goal of employment is feasible through the completion of step one. The second step focuses on five activities: (a) vocational goal, (b) objectives and criteria, (c) case reviews, (d) financial monitoring and follow up, and (e) case closure in self-employment. The counselor and client will need to agree on how to measure progress throughout the case, and this can include quarterly financial reports among other measures. A client's case is not deemed "successful" until she or he has maintained the self-employment vocational goal for at least 90 days. The counselor will have discretion in determining the time frame for deriving the average self-employment income that will be used to assess the client's case for possible closure.

**Definitions of Key Terms**

The following is a definition of *disability* by the U.S. Department of Labor, Office of Disability Employment Policy (2009): "A person with a disability is generally defined as someone who (1) has a physical or mental impairment that substantially limits one or more 'major life activities,' (2) has a record of such an impairment, or (3) is regarded as having such an impairment" (http://www.dol.gov/odep/faqs/federal.htm). The following is the U.S. Census Bureau (2009) definition of a *self-employed worker*:

- Self-employed in own not incorporated business workers. Self-employed in own not incorporated business workers includes people who worked for profit or fees in their own unincorporated business, professional practice, or trade or who operated a farm.

- Self-employed in own incorporated business workers. In tabulations, this category is included with private wage and salary workers because they are paid employees of their own companies. (http:ask.census.gov)

These definitions are included in this section because the various government statistics on individuals with disabilities, employment, self-employment, income, and poverty that are cited throughout this dissertation study also have come from the same government sources, for example, the U.S. Department of Labor (Bureau of Labor Statistics) and the U.S. Census Bureau (Current Population Survey).

# CHAPTER II

# LITERATURE REVIEW

The research literature on self-employment of individuals with disabilities in the U.S. is comprised mostly of nonempirical articles, position or opinion papers, and other nonresearch documents. A small number of empirical-research studies (*n*=12) were found, all of which were published since 1994. Every study used a nonexperimental research design with a largely exploratory purpose and descriptive (i.e., not explanatory or predictive) focus. The most evident and pertinent methodological facet of these studies is their unit of analysis, examining self-employment from the distinct perspectives of either individuals with disabilities or service professionals. Therefore, in the subsequent remaining sections of this chapter, each perspective will be analyzed in turn.

## Individuals' Perspectives of Self-Employment

A review of the small number of U.S. empirical-research studies that examined self-employment from the perspectives of individuals with disabilities indicated the following predominant themes: reasons for self-employment, benefits and challenges of self-employment, and support in self-employment.

*Reasons for self-employment*. The reasons individuals with disabilities pursue self-employment are diverse and vary in complexity. For some, self-employment is a response to discrimination they faced in losing employment or in trying to gain employment (Blanck, Sandler, Schmeling, & Schartz, 2000), or to lack of opportunities in other types of employment (Hagner & Davies, 2002). For some, self-employment is an answer to previous unsatisfactory employment (McNaughton, Symons, Light, & Parsons,

2006) by using those negative experiences working for others to explore working for themselves (McNaughton et al., 2006; Palmer et al., 2000).

Individuals with disabilities may choose self-employment based on a combination of reasons that not only includes elements of business-feasibility assessment, such as resource/support availability and understanding one's circumstances, abilities, and needs, but also more nuanced or idiosyncratic elements of risk-taking, such as chance and timing of life events that provide a self-employment opportunity at a particular moment (Palmer et al., 2000). Still for others, self-employment is simply a matter of choice. Funded by the Rehabilitation Services Administration, the United Cerebral Palsy Association's *Choice Access* demonstration project found 21% of participants had chosen self-employment. Although not based on an empirical-research evaluation of the project, a commonly repeated sentiment by participants was, "It's my choice, it's what I want to do" (Callahan, Shumpert, & Mast, 2002, p.76).

*Benefits of self-employment*. Individuals with disabilities can experience a range of benefits from self-employment. Financial benefits are paramount for some, pursuing financial independence to support themselves and their dependents as a priority even as some face the prospect of only making enough to supplement income from government assistance or other employment they already have (Hagner & Davies, 2002; McNaughton et al., 2006). Others may have a more ambitious goal and plan of not just sustaining or maintaining but expanding their business (Blanck et al., 2000; Hagner & Davies, 2002). Self-employment benefits can also be more intrinsic or intangible, such as individuals having a decision-making role, personal control, sense of dignity, personal competence, work autonomy, self-worth, self-reliance, enjoyment of work, way to meet personal expectations, and work toward changing societal attitudes about individuals with disabilities (Hagner & Davies, 2002; McNaughton et al., 2006).

Other benefits of self-employment for individuals with disabilities have been described in the empirical research literature in terms of the array of opportunities for exploring and pursuing a wide range of small business and entrepreneurial experiences, reflecting a diversity of interests: jewelry sales, gift baskets, toys and painted wood figures, bulk-mailing service, home child-care services, artist, party balloons service, freelance journalist, motivational public speaker, software consultant, and web-site developer (Blanck et al., 2000; Hagner & Davies, 2002; McNaughton et al., 2006; Palmer et al., 2000). These businesses, which sell a number of different products and services across a number of different industries, also indicate a diversity of talent and ability.

*Challenges of self-employment*. A primary and significant self-employment challenge is the access to adequate capital and business financing beyond individual and family resources. While this challenge is certainly not unique to individuals with disabilities, their access to necessary capital and financing from conventional sources, such as commercial banks, has been almost as difficult as it has been historically for women and ethnic-minority groups (Palmer et al., 2000; President’s Committee on Employment of Individuals with Disabilities, 2000). Consequently, individuals with disabilities have relied substantially on individual and family resources, and alternative external funding sources, such as community small-business development organizations, vocational-rehabilitation and disability-services agencies, and grant programs (Blanck et al., 2000; Hagner & Davies, 2002; Palmer et al., 2000).

Individuals with disabilities face a number of challenges in self-employment that are uniquely related to their disability condition and status, including (a) perceived or actual reduction in government benefits due to their self-employment income, (b) societal prejudice, (c) negative public attitudes and low expectations, (d) educational barriers in inadequate school transition and vocational programs, (e) technological barriers in the access and use of devices, and (f) funding policy and regulation barriers in business and personal supports (Callahan et al., 2002; McNaughton et al., 2006; President's Committee on Employment of Individuals with Disabilities, 2000; Rizzo, 2002).

Responding to self-employment challenges can require different skill sets based on factors such as the nature of the business, market conditions, and access to supports and resources. The level of difficulty of the challenges, however, may be related to both the type and severity of an individual's disability and certain contexts of self-employment (Hagner & Davies, 2002). For example, in their qualitative study of eight entrepreneurs with cognitive disabilities, Hagner and Davies (2002) found individuals had expressed that the major disadvantages of self-employment were the labor-intensive nature and difficulty of managing a business, and the difficulty in receiving necessary services and support. Businesses either received subsidies or generated only enough revenues to cover expenses. The owners needed to supplement their income with SSI, Medicaid, and other jobs. Four of the businesses were operated essentially under the auspices of the disability service-provider agency (Hagner & Davies, 2002). Ironically, for individuals with severe disabilities, the years of receiving social services may be contributing to their difficulty in being as self-directed as they can or should be in self-employment (Rizzo, 2002).

*Support in self-employment*. For individuals with disabilities in the U.S., support in self-employment has typically meant relying on a patchwork of resources, including (a) financial assistance from family, disability services and VR agencies, government loans and grants, and community organizations; (b) personal support and services from Social Security and other agencies; and (c) business-related assistance and support from attorneys, accountants, business-development experts, and computer/information technology consultants and technicians (Blanck et al., 2000; Hagner & Davies 2002; McNaughton et al., 2006; Palmer et al., 2000). The availability and accessibility of resources to support individuals with disabilities in self-employment, however, remain foremost concerns. This is a central issue that the Iowa *Entrepreneurs with Disabilities* (EWD) program attempted to address. The evaluation of EWD (see Blanck et al., 2000) is *sui generis* in the empirical-research literature on self-employment of individuals with disabilities in the U.S. and will receive further attention and elaboration here.

The Iowa Entrepreneur's with Disabilities (EWD) was a statewide program supporting the self-employment of individuals with disabilities managed by the Iowa Department of Vocational Rehabilitation Services (DVRS), Iowa Department for the Blind (IDB), and Iowa Department of Economic Development (IDED). From across the state, the program recruited 509 Iowa residents with disabilities who were already receiving services from the DVRS or IDB. After the selection process, 112 individuals were provided financial (typically about $10,000) and technical assistance to start, expand, or maintain their own business. The selected individuals were required to provide at least 50% of business capital. Technical assistance included accounting, legal advice, and business planning and management (Blanck et al., 2000). After the start of the EWD program, most of the selected participants were receiving less government assistance than they had been receiving during the program's selection process.

Businesses were monitored monthly by EWD program and were required to disclose financial information for two years or until they reached self-sufficiency. The program defined success as DVRS case closure, and individuals were eligible for case closure if their business ". . . has received financial assistance, remains in stable operation, and shows a trend toward profitability" (Blanck et al., 2000, pp.1609-1610). From the program period of May 1, 1995 to August 1, 1999, case closures were achieved by 42 individuals. The profiles of these successful cases were as follows: 42 were White, 33 were male, 39 had finished at least high school, 25 owned a service-oriented business, and 17 had an orthopedic primary disability, the largest category.

The preceding review of studies focusing on the self-employment perspectives of individuals with disabilities in the U.S. provides one of two distinct perspectives in the empirical-research literature. The other perspective comes from service professionals.

**Professionals' Perspectives of Self-Employment**

Individuals with disabilities in self-employment often receive support from service professionals, including counselors from vocational rehabilitation (VR) agencies, consultants from small-business development centers (SBDCs), and professionals from other social-service agencies and community organizations. From the empirical-research studies that examined these professionals' perspectives, the predominant themes were: professionals' attitudes about, roles in, and support of clients' self-employment.

*Attitudes about self-employment*. A more positive or favorable attitude toward self-employment by VR counselors has been associated with higher case closures for clients with disabilities in self-employment (Arnold & Seekins, 1996; Ravesloot & Seekins, 1996). Counselors' attitudes toward self-employment tend to be more positive if they have had positive experiences with clients in self-employment (Arnold & Seekins, 1996; Ravesloot & Seekins, 1996). Agency policies also can affect agency atmosphere and counselors' attitudes (Arnold & Seekins, 1996; Ravesloot & Seekins, 1996).

Some researchers have posited that for decades in the U.S., a core VR philosophy has been to help individuals with disabilities find traditional wage and salary jobs working for others, not self-employment, because counselors are not trained in business development (Colling & Arnold, 2007; Schriner & Neath, 1996). That may be changing, however. In examining policy changes in self-employment from 1992 to 2002, Arnold and Ipsen (2005) found, "Current policies are more positive toward self-employment" (p.117). On average, more necessary components of self-employment (e.g., market analysis, business plan) were addressed in 2002, which also provided more guidance to counselors on self-employment initiation and follow-through by coordinating activities with small-business development professionals than in 1992 (Arnold & Ipsen, 2005).

Service region may affect VR counselors' attitudes toward self-employment. For example, Ravesloot and Seekins (1996) found in a survey of counselors from U.S. rural and urban areas that rural counselors rated self-employment statistically significantly higher. Rural counselors also were significantly more familiar with processes involved in self-employment. Counselors did not significantly differ on most ratings of what they believed to be critical self-employment attributes: enthusiasm, persistence, intelligence, risk-taking, business-planning ability, their own financial backing, pleasing personality, and good organizational and social skills. Urban counselors, however, rated a client's experience in considering what type of business to own to be significantly more important (Ravesloot & Seekins, 1996). While urban counselors expressed significantly greater satisfaction with clients' employment, training, and educational opportunities, rural counselors expressed greater dissatisfaction with transportation options available to clients, but also expressed greater satisfaction with networking opportunities available to counselors (Arnold & Seekins, 1997). If a problem was identified by both rural and urban counselors, it was usually perceived worse by the former: "Rural counselors work in situations that are less conducive to achieving VR goals" (Arnold & Seekins, 1998, p.12).

In the field of supported-employment in the U.S., professionals' attitudes toward self-employment of individuals with disabilities have been generally characterized by (a) fear that individuals would be in a solitary environment and socially isolated, (b) concern over not being able to provide adequate information to individuals about starting and maintaining a business, (c) belief that a large majority of business ventures fail in their first year, and (d) caution that the direction and decision for self-employment not be confused with the service provider's personal wish to be a business owner (Callahan et al., 2002). These attitudes can be traced through the history of supported employment in the U.S., which before the 1990s rarely included self-employment as a service outcome. When it was, Callahan et al. (2002) noted that self-employment was ". . . largely characterized by either retail businesses developed as a result of governmentally mandated 'set-asides' for persons with milder impact of disability in their lives (particularly from blindness) or in telemarketing of household goods by persons with more significant physical disabilities" (p.76).

*Role in self-employment*. In recent years, approximately 12% of working individuals with disabilities have earned an income from self-employment (Ipsen, Arnold, & Colling, 2005). While many of those individuals have been supported as clients by VR agency services, since the late 1980s, the national VR case-closure rates in self-employment have generally remained between 2% and 3% (Ipsen, Arnold, & Colling, 2005; Schriner & Neath, 1996). These rates represent the ratio of successful VR case closures in self-employment to the total number of VR employment case closures.

Despite the relative stability of the national VR self-employment closure rates over the last two decades, an analysis of the "Rehabilitation Services Administration 911 Closure Reports for Fiscal Years 2003 to 2007" by Revell, Smith, and Inge (2009) found differences in self-employment rates among states (50 states and D.C., "General and Combined" VR agencies). In Fiscal Year (FY) 2007, Mississippi had the highest case closure rate in self-employment at 12.6%, followed by Wyoming 7.9%, Alaska 6.6%, and Maine 6.0%. In fact, Mississippi had the highest rates over these fiscal years. In FY 2007, the national average-weekly self-employment earnings of $396 were higher than the average-weekly earnings of $350 for all Status 26 closures (VR defines employment closure as "rehabilitated"). By comparison, in FY 2007, Mississippi had average-weekly self-employment earnings of $439 and average-weekly earnings of $423 for all Status 26 closures. Connecticut had the highest self-employment average-weekly earnings of $896 and in all Status 26 closures of $538 (Revell, Inge, & Smith, 2009).

The role of VR counselors in clients' self-employment may vary by location. For example, Arnold and Seekins (1995) found several statistically significant differences between counselors in U.S. rural and urban areas: (a) self-employment was used more commonly in VR case closures in rural areas; (b) rural counselors averaged more self-employment closures during their careers; and (c) job availability, slower growth rate, higher unemployment, and lower wages contributed to greater closure likelihood in rural settings (Arnold & Seekins, 1995; see also Seekins, 1992). Counselors did not differ significantly in their caseload, level of education, years as counselor, or access to telephones and fax machines (Arnold & Seekins, 1998; see Arnold & Seekins, 1997, and Arnold & Seekins, 1995), but rural clients lived significantly farther than urban clients did from their counselors' offices (Arnold & Seekins, 1997).

*Support of self-employment*. Service professionals have cited service costs and agency resources as important considerations in supporting self-employment of clients. In their focus group, Colling and Arnold (2007) found that professionals ". . . cited budgetary constraints, limited personnel, and diminishing resources as a reality of service delivery today" (p.38). VR counselors' decision to support self-employment may also be influenced by their consideration of ". . . how long such placements last compared to others, the comparative return on investment, the levels of income produced by each placement type, or consumers' comparative satisfaction" (Arnold & Seekins, 1996, p.17). Others have expressed concerns that VR counselors are neither adequately trained nor equipped to provide resources and support to clients in self-employment (Hagner & Davies, 2002), while also cautioning that VR counselors' final decision to support self-employment desires and goals could be based more on their assessment of clients' disability status than on business-related factors (Rizzo, 2002). Notably, self-employment rates have been higher for individuals with disabilities outside the VR system (Presidents Committee on Employment of People with Disabilities, 2000).

As service providers and agencies face resource constraints, multi-agency collaboration may provide a way of pooling expertise and finances to support individuals with disabilities in self-employment. Colling and Arnold (2007) found from their focus group interviews that interagency collaboration ". . . could provide direct results for clients such as entrepreneurship training and increased the probability of a successful business" (p.38). They also found, however, that professionals admitted knowing little about each other, and cited physical and organizational barriers as discouraging active collaboration. Moreover, those with collaboration experience did not characterize their relationships as active or engaged, and cited financial and funding-source accountability as a collaboration barrier. On one side, rehabilitation counselors ". . . expressed apprehension that small businesses or self-proprietorships may not lead to strong performance on the identified standards and indicators for which their programs are evaluated" (p.38). On the other side, professionals from small-business development centers (SBDCs) expressed concerns that clients' businesses that were smaller and contributing less to their "bottom-line" than businesses they typically funded.

For VR counselors, success may entail aligning clients' individualized needs and reasons for self-employment, such as (a) increasing self-confidence and engaging in meaningful work, (b) increasing self-sufficiency and income, (c) resolving concerns over accommodations and mobility, (d) increasing control over scheduling and amount of work, and (e) increasing community inclusion and participation (Walls et al., 2001). Hagner and Davies (2002) recommend counselors receive self-employment training to help clients make informed choices and (a) understand how self-employment can benefit them, (b) recognize the types of supports needed for self-employment success, and (c) assist clients to identify reasons for choosing self-employment over other employment.

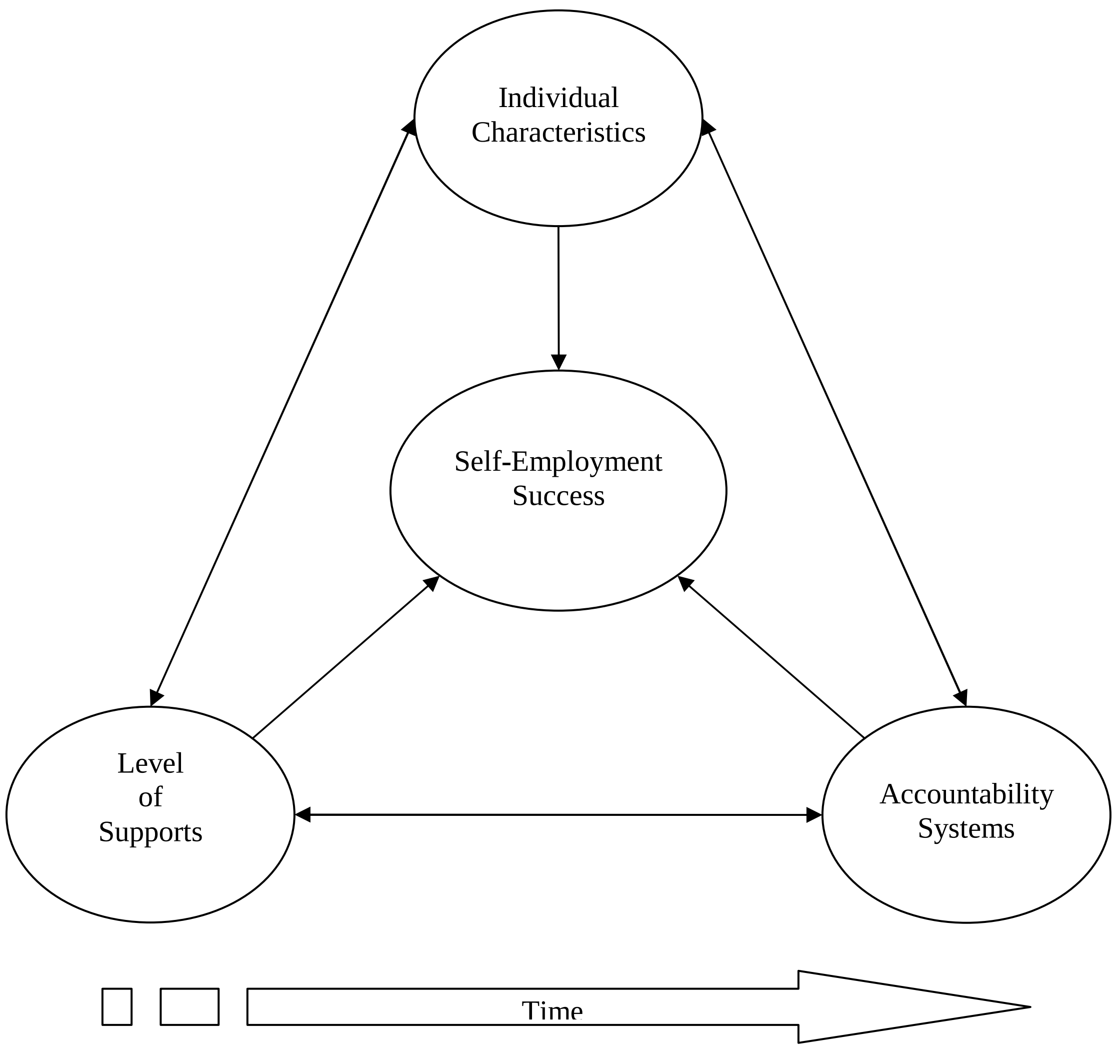
Incorporating elements of person-centered-planning may be helpful for service professionals supporting clients in self-employment (Rizzo, 2002). This approach typically involves service professionals recognizing clients' strengths and skills, around which a number of external (e.g., accounting), organizational (e.g., advisory councils), and other personal supports are built. Professionals also may want to discuss with clients contextual factors such as (a) understanding individual circumstances, abilities, and needs; (b) evaluating assumptions about self-employment; and (c) recognizing actual, available support and training resources (Palmer et al., 2000). Ultimately, as Arnold and Ipsen (2005) assert, "There is no cookie-cutter method for achieving a self-employment outcome. Each agency's policy and set of operational procedures are unique, reflecting the state's fiscal constraints and its approach to self-employment" (p.117).

**Conceptual Framework**

My review of the empirical-research literature indicates that individuals with disabilities can succeed in self-employment, and that their success is influenced most by three factors: individual characteristics, level of supports, and accountability systems. Presented in Figure 1, the conceptual framework for this dissertation study is based on the core assumption that self-employment success links individuals with these three interrelated and interdependent factors over time. While success is often judged in business terms by measures such as income and profits, growth, and market share, success can also include other more intrinsic measures, such as the acquisition of skills, and enhanced self-determination and self-efficacy. Individual characteristics constitute person-level traits or identities not limited to demographic variables such as gender and ethnicity. Level of supports constitutes the amount or degree of assistance to individuals with disabilities that is directly and indirectly related to their business ownership and management, for example, government aid (e.g., Medicare, Social Security), business loans, and VR services. Accountability systems constitute laws and regulations, and business requirements and conditions related to the business venture, such as income and profits, local market competition, and business loan-repayment schedule.

The conceptual framework for this dissertation study not only assumes changes in the relationships, both direct and mediated, among the three factors and their relationship to self-employment success over time, but also that the rate of change is not expected to be consistent or predictably linear but dynamic. This is recognition of the uniqueness of each individual self-employment experience. For example, individuals with disabilities who are female and a member of an ethnic minority group may face difficulties based on their characteristics that other individuals with disabilities in self-employment do not face. Individual characteristics, then, can mediate the relationship between level of supports and accountability systems, where lower resource allocation based on gender or ethnicity affects business activity and practices and affects success. Level of supports can mediate the relationship between individual characteristics and accountability systems. For example, diminished resources or decreased supports resulting from a recession can affect business practices and revenue and the ability of individuals to meet loan requirements or obtain necessary supports related to their disability condition, thereby affecting success. Accountability systems can mediate the relationship between individual characteristics and level of supports. For example, changes in the local market, such as an increase in the number of similar businesses or new laws and regulations, can significantly shape business practices and activities. These conditions, then, can affect the level of resource allocation that is necessary for supporting a business and affect success.

Figure 1. Conceptual model of self-employment success and its most influential factors



CHAPTER III

METHOD

The procedures for conducting this dissertation research study comprised five major steps: (a) defining the research purpose and questions, (b) designing the research study, (c) collecting the data, (d) defining the data variables, and (e) analyzing the data.

## Research Purpose and Questions

In alignment with the conceptual framework, <u>the purpose of this dissertation research study</u> was to examine individuals with disabilities in self-employment through vocational-rehabilitation (VR) agencies across the U.S. by addressing these six *a priori* research questions:

(1) What are significant predictors of self-employment case closure for VR clients?

(2) Do significant predictors of self-employment case closure for VR clients differ over time?

(3) Do significant predictors of self-employment case closure for VR clients differ depending on service location (e.g., different U.S. states or regions)?

(4) What is the relationship of individual characteristics, level of supports, and accountability systems to self-employment success?

(5) Does the relationship of individual characteristics, level of supports, and accountability systems to self-employment success differ over time?

(6) Does the relationship of individual characteristics, level of supports, and accountability systems to self-employment success differ by location?

## Research Design

To answer the research questions, I used a nonexperimental research design, consisting of statistical analyses of extant data (see Shadish, Cook, & Campbell, 2002). The goal of this approach to research design is noted by Kerlinger and Lee (2000):

> Nonexperimental research is systematic empirical inquiry in which the scientist does not have direct control of independent variables because their manifestations have already occurred or because they are inherently not manipulable. Inferences about relations among variables are made, without direct intervention, from concomitant variation of independent and dependent variables. (p.558)

Moreover, nonexperimental research is often used when investigating a phenomenon for which experimentation would be premature because it lacks an empirical basis, and that the phenomenon needs to be better understood first through exploration of a number of possible variable relationships in statistical analyses (Shadish et al., 2002). In this dissertation study, that exploration consisted of analyzing extant administrative data from VR agencies across the U.S. as they play a visible role in the self-employment of individuals with disabilities observed throughout the empirical-research literature.

**Data Collection**

As a federal agency within the U.S. Department of Education Office of Special Education and Rehabilitative Services, the Rehabilitation Services Administration (RSA) was the source of the extant administrative VR data analyzed in this dissertation study. The RSA collects data from VR agencies in all 50 states, the District of Columbia, and the territories. The data are collected for each fiscal year (FY), the government's operating calendar beginning on October 1 of one year and ending on September 30 of the following year. These fiscal-year data are called "RSA-911 Case Service Report" and are submitted in disk, CD-ROM, or electronic format by every agency in November, after the end of a fiscal year. The RSA provides assistance in the form of editing programs to ensure accuracy of data entry by state VR agencies.

After requesting and receiving the <u>deidentified RSA data</u> for FY 2003 to 2007, the data, which were contained in several CD-ROM discs, were opened in a secure computer and transferred as text files to the hard drive. The data then were transferred to the PASW Statistics GradPack 17.0 for Windows (SPSS, Inc., 2009) statistical software to compile the data, label the variables according to the RSA data-variable dictionary, and analyze the data. Only data from U.S. states and District of Columbia for VR clients with disabilities who achieved employment case closure were included in these analyses. The territories were excluded because of their legal, political, and socio-cultural differences from the states and because they are not designated as part of the four U.S. Census Bureau Regions, which were to be analyzed in this dissertation research study.

**Data Variable Definitions**

Included in the statistical analyses of the RSA data for FY 2003 to 2007 in this dissertation research study are some of the 43 variables contained in the RSA data and two external variables. The RSA variables were defined according to its data-variable dictionary (Rehabilitation Services Administration, 2005). The type and number of selected variables were based on my review of the empirical-research literature (see Chapter II: Literature Review), the conceptual framework for this dissertation study, and model parsimony. Thus, the variables that best represented self-employment success, individual characteristics, level of supports, and accountability systems were selected, while also taking care to avoid variable redundancy and data fishing/mining.

Four demographic categorical variables representing VR clients' individual characteristics were selected: (a) gender, with categories of male coded as 0 and female coded as 1; (b) ethnicity, with categories of nonwhite coded as 0 and white coded as 1; (c) significant-disability status, with categories of no coded as 0 and yes coded as 1; and (d) educational attainment at case closure, with categories of up-to-high school coded as

0 and post-high school coded as 1. These four variables were the most frequently cited individual characteristics in the empirical-research literature review, and they also represent the most fundamental and important characteristics to empirically analyze in their relationship to self-employment success for VR clients.

Acknowledging their distinctions, racial and ethnic identities (e.g., white, Hispanic) both were included in the "ethnicity" variable as intended by the RSA. Clients with biracial identification were coded as 1 in the white and nonwhite categories. Also, the nonwhite category included Black or African-American, Latino or Hispanic, Asian, Native Hawaiian or Other Pacific Islander, and American Indian or Alaska Native.

The significant-disability (status) variable is defined by the RSA (2005) as:

> An individual with a significant disability is an individual: (a) who has a physical or mental impairment that seriously limits one or more functional capacities (such as mobility, communication, self-care, self-direction, interpersonal skills, work tolerance, or work skills) in terms of an employment outcome; (b) whose VR can be expected to require multiple VR services over an extended period of time; and (c) who has one or more physical or mental disabilities resulting from amputation, arthritis, autism, blindness, burn injury, cancer, cerebral palsy, cystic fibrosis, deafness, head injury, heart disease, hemiplegia, hemophilia, respiratory or pulmonary dysfunction, mental retardation, mental illness, multiple sclerosis, muscular dystrophy, musculo-skeletal disorders, neurological disorders (including stroke and epilepsy), spinal cord conditions (including paraplegia and quadriplegia), sickle cell anemia, specific learning disability, end-stage renal disease, or another disability or combination of disabilities determined on the basis of an assessment for determining eligibility and VR needs to cause comparable substantial functional limitation. (p.43)

Four variables representing accountability systems were selected: (a) total cost of VR services, (b) average weekly earnings at closure, (c) typical weekly hours worked at closure, and (d) state average annual unemployment rate. The total cost of VR services represented accountability of clients to VR for service costs, working toward closure. The variable also represented accountability of VR counselors to their agency for money spent on a client’s case. The average weekly earnings variable represented accountability of clients to VR for earning sufficient money from employment to lead to closure. The typical weekly hours worked variable represented accountability of clients to their work (e.g., customers), as an indication of their commitment to working for earnings to achieve closure. The state’s average unemployment rate variable represented accountability in terms of a state’s overall economic condition in which the clients worked, shaping a business environment that then directly affected the employment earnings of clients.

The cost of VR services included, to the nearest dollar, the amount of money the state VR had spent on a client’s services for the entire case, excluding administrative costs and nonindividual services. The average weekly earnings included, to the nearest dollar, the amount of money a client had earned from employment in a typical week at closure. Earnings could include wages, salaries, commissions, and tips before payroll taxes were deducted; they also could include self-employment profits. These earnings were based on adjusted gross income (income minus unreimbursed business expenses), but excluded in-kind payments such as lodging and meals. If earnings exceeded $9999, then “9999” was entered in the data field. No negative earnings could be reported; the lowest amount that could be reported was “0000” for no earnings. The typical weekly hours worked included the number of hours a client had worked for earnings during a typical week at closure. If a client’s work hours exceeded 99 hours in a week, then “99” was entered in the data field. The state’s average annual unemployment rate, one of two variables external to the RSA data, was a state’s quarterly rates that had been averaged for each year by the U.S. Department of Labor from 2003 to 2007. The unemployment rate data were manually entered and incorporated with the RSA data.

Three variables representing level of supports were selected: (a) number of VR services, (b) monthly dollar amount of public supports at closure, and (c) number of medical support services at closure. The number of VR services variable represented the actual services and their quantifiable level of VR support for clients. The monthly dollar amount of public supports variable represented the level of external public financial assistance supporting clients during the case. Similarly, the number of medical support services variable represented the level of medical/health support for clients; an array of medical services related to clients' disability and concomitant health condition requiring these services in order for them to be able to perform self-employment work tasks.

The number of VR services included all services provided during the entire case. These services could include, for example, job searching and skills training, which were among the pre-defined categories, but other services also could be identified and included by counselors. The monthly dollar amount of public supports at closure included, to the nearest dollar, the amount of money a client had received from government and other public sources, including Social Security and Temporary Assistance to Needy Families. If a client's public support exceeded $9999 at closure, then, "9999" was entered in the data field. The number of medical support services at closure included all medical services and insurance coverage the client had at closure, including Medicare and Medicaid, and any other public and private health insurance plans or programs.

The other variable external to the RSA data was the U.S. Census Bureau Regions. All states and D.C. were coded as belonging to one of four regions, coded 1 for Northeast, 2 for Midwest, 3 for South, and 4 for West. Finally, the binary outcome (criterion) variable was employment-closure status, whether a client's case was closed in self-employment or other employment. A client was coded 0 for closure in other employment and coded 1 for closure in self-employment. Therefore, in this dissertation study, “self-employment success” was defined as VR self-employment case closure.

**Data Analysis**

A two-step process was used in the analyses of the RSA data. First, the data were screened to examine their distributions, producing a case summary and descriptive statistics. Next, the data were statistically analyzed using Hierarchical Linear Modeling (HLM) and Structural Equation Modeling (SEM) to answer the research questions. These analyses contained most but not all of the same variables. This difference reflected my consideration of the empirical-research literature review, the conceptual framework for this dissertation study, and the model-parsimony necessities to avoid variable redundancy (i.e., the best models with the fewest variables) and to disallow data fishing/mining.

*Data screening*. Each RSA fiscal-year dataset was screened. This involved inspecting cases and variables for impossible values, such as those that may have occurred because of a keystroke error (e.g., a “211” for gender or ethnicity). Data of continuous variables were screened for univariate and multivariate normality.

Data were also screened with the Missing Values Analysis in PASW 17.0 (SPSS, Inc., 2009) to determine the amount, pattern, and nature of missing data. A univariate pattern occurs when data are missing for one variable; an arbitrary pattern occurs for any variable; and a monotone pattern occurs when items or variable groups are missing, such as attrition with repeated measurements (Schafer & Graham, 2002). The nature of missing data are classified as (a) Missing Completely At Random – MCAR; or (b) Missing At Random – MAR; or (c) Missing Not At Random – MNAR (Schafer &

Graham, 2002). For MCAR data, the probability of missing data does not depend on the distributions of either the observed or unobserved data (i.e., missing values). For MAR data, the probability of missing data depends on the distribution of the observed data but not on the unobserved data. For MNAR data, the probability of missing data depends on the distribution of the unobserved data (Schafer & Graham, 2002). Researchers have noted, however, that "There are as yet no firm guidelines for how much missing data can be tolerated for a sample of a given size" (Tabachnick & Fidell, 2007, p.63). A case summary and the descriptive statistics of variables were produced to examine the data distributions across the five fiscal years, FY 2003 to 2007.

*HLM statistical modeling.* To answer the first three research questions, the RSA data were exported to the statistical-software program, Hierarchical Linear Modeling, version HLM 6.0.8 (Raudenbush, Bryk, & Congdon, 2009). The data were hierarchically structured, or nested, as they were ". . . organized at more than one level" (Tabachnick & Fidell, 2007, p.781). The statistical analytic approach of HLM (Raudenbush et al., 2009) is known as multilevel modeling (Raudenbush & Bryk, 2002; Tabachnick & Fidell, 2007). Hierarchical linear modeling specifically refers to the proprietary software by Raudenbush et al. (2009), in which ". . . each of the levels in this structure is formally represented by its own submodel. These submodels express relationships among variables within a given level, and specify how variables at one level influence relations occurring at another" (Raudenbush & Bryk, 2002, p.7). Hierarchically structured data need to be analyzed at different levels to avoid errors in (a) using degrees of freedom that are not available, violating the statistical assumption of independence, and inflating the Type I error rate; and (b) research interpretations by erroneously applying group-level analysis to the individual, known as “ecological fallacy,” (Tabachnick & Fidell, 2007, p.782), or applying individual-level analysis to the group level, known as “atomistic fallacy” (Hox, 2002, as cited in Tabachnick & Fidell, 2007, p.782).

A two-level hierarchical generalized linear model (HGLM) was produced for each fiscal year. This model is a special type of HLM analysis, a nonlinear analysis of binary or multinomial outcome (criterion) variables with count/ordinal data (Raudenbush & Bryk, 2002). In this HGLM analysis, clients were “nested” in their home state where they received VR services, and either achieved case closure in self-employment (coded as 1) or closure in other employment (coded as 0) that occurred after a consecutive 90-day case employment period. The use of HGLM to analyze a binary outcome variable “. . . offers a coherent modeling framework for multilevel data with nonlinear structural models and nonnormally distributed errors” (Raudenbush & Bryk, 2002, p.292).

The level-1 model of any HGLM contains three parts: sampling model, nonlinear link function, and structural model. The sampling model is $Y_{ij} \mid \phi_{ij} \sim B(m_{ij}, \phi_{ij})$, where $Y_{ij}$ is the number of successes with a binomial distribution in $m_{ij}$ number of trials and $\phi_{ij}$ probability of success (Raudenbush, Bryk, Cheong, Congdon, & du Toit, 2004). The expected value of $Y_{ij}$ is $E(Y_{ij} \mid \phi_{ij}) = m_{ij}\phi_{ij}$ and variance is $Var(Y_{ij} \mid \phi_{ij}) = m_{ij}\phi_{ij}(1-\phi_{ij})$. Because $m_{ij}$ =1, $Y_{ij}$ may take on values of 1 or 0. This sampling model then becomes a special type of binomial distribution, called a Bernoulli distribution (Raudenbush & Bryk, 2002; Raudenbush et al., 2004). The sampling model for the Bernoulli distribution is rewritten as: $\text{Prob}(Y_{ij} = 1 \mid \beta_j) = \phi_{ij}$. The nonlinear link function is $\eta = \log\left(\frac{\phi_{ij}}{1-\phi_{ij}}\right)$, which is a logit or log odds link function used to transform the predicted value, $\eta$, as nonlinear (Raudenbush et al., 2004). In this dissertation study, the link function represented the log odds of VR clients achieving self-employment closure, where $\phi_{ij}$ represented the probability of achieving self-employment closure with values between 0 and 1, and where 1-$\phi_{ij}$ represented the probability of achieving other employment closure. Finally, the level-1 structural model comprised two steps. First, an unconditional model was specified in which the log odds of self-employment closure were analyzed as an intercept without predictors. Second, a conditional model was specified in which the log odds of self-employment were analyzed with predictors. This two-step process is recommended by Raudenbush et al. (2004). The unconditional level-1 structural model is written as $\eta = \beta_{0j}$, where $\beta_{0j}$ is the intercept. The conditional level-1 structural model is:

$$\eta_{ij} = \beta_{0j} + \beta_{1j}(Gender)_{ij} + \beta_{2j}(Ethnic)_{ij} + \beta_{3j}(CostVR)_{ij} + \beta_{4j}(EducAtt)_{ij} + \beta_{5j}(PubSupp)_{ij} + \beta_{6j}(SigDisab)_{ij}$$

The level-1 structural model included an outcome variable, $\eta_{ij}$, representing the log odds of VR clients in self-employment at closure. The six level-1 predictors, $X_{ij}$, included gender, ethnicity, cost of VR services received, level of educational attainment at closure, dollar amount of public supports at closure, and significant-disability status. The *CostVR* and *PubSupp* predictors were centered with the group (i.e., state) mean. Centering is used when 0 is not a meaningful value and to ensure stable estimation of parameters (Raudenbush & Bryk, 2002). The subscript *i* referred to the VR client, the level-1 unit of analysis. The subscript *j* referred to the state, the level-2 unit of analysis. The six slopes, $\beta_{1j}$ to $\beta_{6j}$, represented the change in the log odds of self-employment closure associated with a unit increase in the corresponding predictor, $X_{pij}$, holding constant (i.e., controlling the effects of) the other predictors.

The HGLM at level-2 further analyzed each level-1 coefficient $\beta$ as its own "outcome" variable. At level-2, the unconditional model is $\beta_{0j} = \gamma_{00} + u_{0j}$. The $\gamma_{00}$ intercept represented the mean log odds of self-employment closure across states. The $u_{0j}$ term represented the random effect (residual variance), which was the amount of variability among states in their mean log odds of self-employment closure.

<u>Conditional Level-2</u>: $\beta_{0j} = \gamma_{00} + \gamma_{01}(AvgUnemp) + u_{0j}$

$\beta_{1j} = \gamma_{10}$ {level-1 *Gender* predictor}

$\beta_{2j} = \gamma_{20}$ {level-1 *Ethnic* predictor}

$\beta_{3j} = \gamma_{30}$ {level-1 *CostVR* predictor}

$\beta_{4j} = \gamma_{40}$ {level-1 *EducAtt* predictor}

$\beta_{5j} = \gamma_{50}$ {level-1 *PubSupp* predictor}

$\beta_{6j} = \gamma_{60}$ {level-1 *SigDisab* predictor}

In the conditional level-2 model, the lone predictor was *AvgUnemp*, a state's average annual unemployment rate. This predictor was grand-mean centered. The $\gamma_{00}$ intercept term represented the mean log odds of self-employment closure for a nonwhite male client who had received his home state's average cost of VR services, whose educational attainment at closure was no more than a high-school level, who received his state's average dollar amount of public supports at closure, who identified as not having a significant disability, and who lived in a state with a "typical" self-employment closure rate, a random effect $u_{0j}$ value of 0. The $u_{0j}$ term represented random variation of the intercept, $\gamma_{00}$, across states, controlling for *AvgUnemp*. The $\gamma_{01}$ slope term represented the change in the log odds of self-employment closure associated with a unit increase in the unemployment rate for states with the same $u_{0j}$ value. The remaining six terms, level-1 slopes $\beta_{1j}$ to $\beta_{6j}$, became level-2 "outcome" variables with intercepts, $\gamma_{10}$ to $\gamma_{60}$ respectively, but without the *AvgUnemp* predictor. These intercepts represented the mean change in the log odds of self-employment closure for VR clients in the same state who differed by one unit on the predictor, $X_{1j}$ to $X_{6j}$, holding constant the other five $X_{ij}$ predictors and the $u_{0j}$ value. These six slope coefficients, then, were tested in the model as fixed effects at level-2, invariant across states (see Raudenbush & Bryk, 2002; Raudenbush et al., 2004). The level-1 and level-2 conditional models produced the following combined complete model:

$$\begin{aligned}\eta_{ij} &= \gamma_{00} + \gamma_{01}(AvgUnemp_{ij} - GrandMeanAvgUnemp_{ij}) + \gamma_{10}(Gender)_{ij} + \\ &\gamma_{20}(Ethnic)_{ij} + \gamma_{30}(CostVR_{ij} - GroupMeanCostVR_{ij}) + \gamma_{40}(EducAtt)_{ij} + \\ &\gamma_{50}(PubSupp_{ij} - GroupMeanPubSupp_{ij}) + \gamma_{60}(SigDisab)_{ij} + u_{0j}\end{aligned}$$

The combined model represented all of the variables for individual characteristics, but only two of three variables for level of supports and only one of three variables for accountability systems. My final selection decision for the predictors was based on model parsimony for this HGLM analysis, to use as few variables as necessary for the model to explain the RSA data across the fiscal years, and guided by a priori belief that the variables representing individual characteristics were the most important ones to test.

Two results are produced in any HGLM, parameter estimates for a unit-specific model and parameter estimates for a population-average model. Choosing a model as the final result of the analysis is based upon the research questions specified for the analysis (Raudenbush & Bryk, 2002; Raudenbush et al., 2004), as suggested by the model names. For this dissertation study, the unit-specific model was chosen because it would answer, for example, the question of how a state's average annual unemployment rate might affect log odds or likelihood of self-employment closure, holding constant the other predictors and the level-2 random effect value, $u_{0j}$. A population-average model would answer a different question, for example, of how unemployment or how being male versus female affects the nationwide log odds or likelihood of self-employment closure, holding constant the other predictors but not $u_{0j}$, the random effects across states.

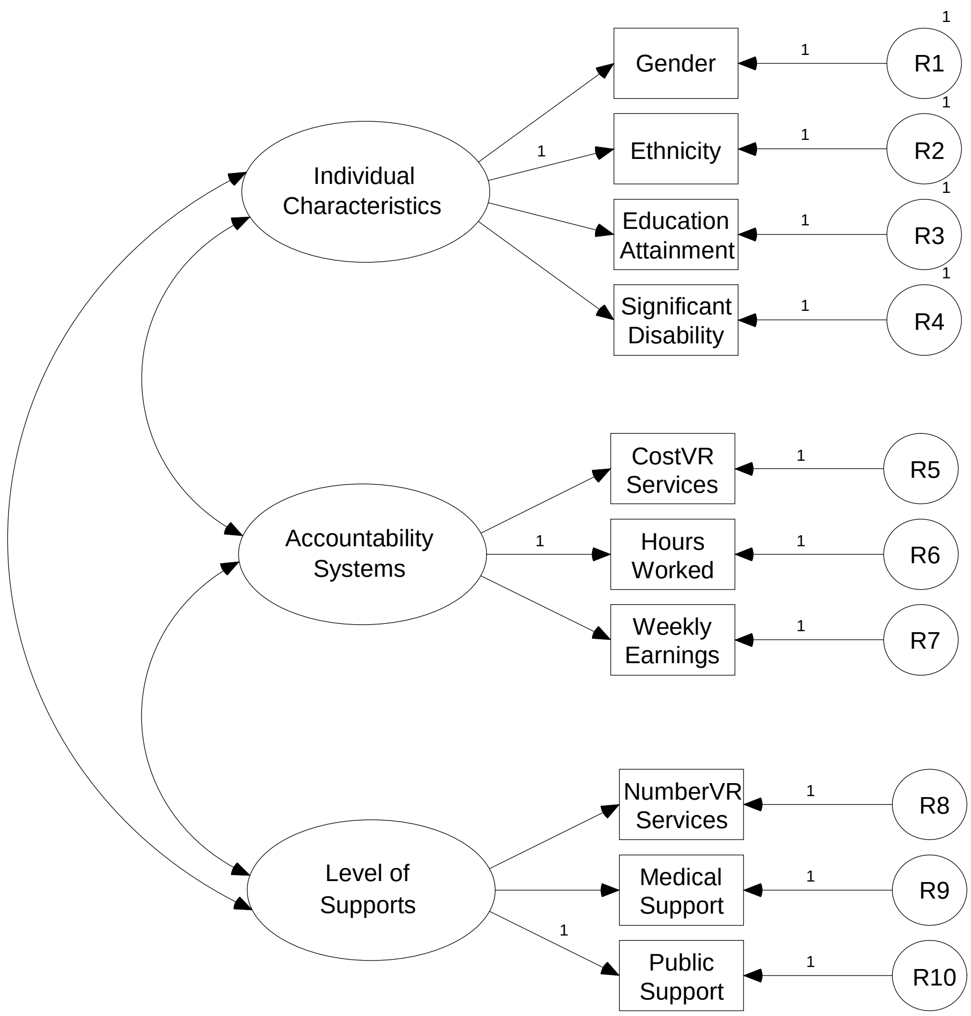
For the unit-specific results, model-based standard errors and robust (or Huber corrected) standard errors were compared. Considerable divergence between these errors is an indication of misspecification in the distribution of $u_{0j}$ random effects, which would affect inferences about the $\gamma_{xx}$ regression coefficients (Raudenbush & Bryk, 2002). Finally, the results were examined to assess how closely the level-1 variance followed the assumed variance of the sampling model, $m_{ij}\phi_{ij}(1-\phi_{ij})$ to determine either over-dispersion (i.e., more than expected) or under-dispersion (i.e., less than expected) with level-1 scalar variance, $\sigma^2 w_{ij}$, (Raudenbush et al., 2004). All model parameters were estimated with Penalized Quasi-Likelihood, a type of estimation that is ". . . based on normal approximation to the restricted likelihood" (Raudenbush, et al., 2004, p.103).

*SEM statistical modeling*. To answer the final three research questions, the RSA data were exported to the Amos 17.0.2 statistical software (Arbuckle, 2008) for analysis with a type of Structural Equation Modeling (SEM) technique known as Confirmatory Factor Analysis (CFA). The CFA model focused on the three factors of self-employment success in the conceptual model: individual characteristics, level of supports, and accountability systems. Only clients with self-employment closure across the fiscal years were included. These individuals achieved “self-employment success” as defined by VR, corresponding to the conceptual model for this dissertation study. The use of CFA is appropriate “. . . when the researcher has some knowledge of the underlying latent variable structure. Based on knowledge of theory, empirical research, or both, he or she postulates relations between the observed measures and the underlying factors a priori, and then tests this hypothesized structure statistically” (Byrne, 1998, p.6).

A full latent variable CFA model was specified and tested with a measurement model linking the observed variables to a factor and a structural model linking the three factors to each other (see Byrne, 1998). In the measurement model, the observed variables are “reflective indicators” (Kline, 2005, p.167), which are theorized to be “caused” by two sources, their residuals (or error terms) and the factors. These factors are unobserved (or latent) variables. The indicators are endogenous variables because their “cause” is explained within the model, loading on a specified factor. In the structural model, the factors are exogenous variables because they contribute to changes in the values of other factors, but their own “cause” is external to the model (Byrne, 1998).

The measurement model for each fiscal year included specifying ethnicity, gender, educational attainment, and significant disability status as four indicators of the individual characteristics factor. The cost of VR services, hours worked at closure, and weekly wages at closure variables were specified as three indicators of the second factor, accountability systems. The number of VR services received, dollar amount of public supports received, and number of medical supports were specified as three indicators of the third factor, level of supports. These indicators were selected because, as described previously (see Chapter III: Methods), they best represent, out of the variables in the RSA data, important theoretical underlying facets of their corresponding factor (see Byrne, 1998; Kline, 2005). This three-factor CFA model is depicted in Figure 2.

Figure 2. Three-Factor CFA Model of Self-Employment Success for Individuals with Disabilities through VR from FY 2003 to FY 2007




With 10 measured variables, 10(10+1)/2 = 55 variances and covariances were estimable (see Byrne, 1998; Kline, 2005). In the specified CFA model, 19 parameters were estimated: 7 direct regression paths from indicators to factors (loadings), 6 indicator residual variances, 3 factor covariances, and 3 factor variances. One regression path for each factor was fixed to a value of 1.0, the “unit loading identification” or ULI constraint (Kline, 2005, p.170) for the unstandardized coefficients required for model identification and scaling (i.e., assigning a metric). Residual variances for the categorical indicators were also constrained to 1.0 (Arbuckle, 2008; Arbuckle, 2009). These constraints were not estimated. Thus, model degrees of freedom (*df*) were computed as 36 (55 minus 19), producing a recursive model that was over-identified, a requirement for obtaining an admissible model solution with more data observations (*df*) than parameters freely estimated (Byrne, 1998; Kline, 2005). All CFA model parameters were estimated with Bayesian Estimation using the Markov-Chain Monte Carlo algorithm (Arbuckle, 2009).

The specified three-factor CFA model was also diagrammed as a mathematical model using the Linear Structural Relationships or LISREL symbolic notation (Jöreskog & van Thillo, 1972; Jöreskog & Sörbom, 2009), which is based on matrix algebra. The mathematical equation representing the general LISREL model for this CFA was: $x = \Lambda_X \Phi + \Theta_\delta$. In the equation, *x* represented each observed indicator variable, and the three parameter matrices represented (1) Lambda $\Lambda_X$ matrix of coefficients of the relationships between each observed indicator variable and its corresponding factor; (2) Phi $\Phi$ matrix of the variances and covariances of factors; and (3) Theta-Delta $\Theta_\delta$ matrix of the variances and covariances of residual terms. In the diagrammed matrices, the Roman letters denoted the observed endogenous variables ($x_1$ to $x_{10}$); the upper-case Greek letters denoted the three parameter matrices. The internal elements of the three parameter matrices were denoted by lower-case Greek letters, representing the estimated parameters. The 0 values indicated that no estimates were specified. The 1 values represented the required constraints. The numeric subscripts indicated the row and column positions, respectively. The Phi and Theta-Delta matrices contained only the lower triangle because the upper triangle was redundant (e.g., $\phi_{21}$ and $\phi_{12}$).

Measured variables $\qquad$ $\Lambda$ Lambda matrix $\qquad$ $\Phi$ Phi matrix {lower triangle}

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \\ x_8 \\ x_9 \\ x_{10} \end{bmatrix} = \begin{bmatrix} \lambda_{11} & 0 & 0 \\ 1 & 0 & 0 \\ \lambda_{31} & 0 & 0 \\ \lambda_{41} & 0 & 0 \\ 0 & \lambda_{52} & 0 \\ 0 & 1 & 0 \\ 0 & \lambda_{72} & 0 \\ 0 & 0 & \lambda_{83} \\ 0 & 0 & \lambda_{93} \\ 0 & 0 & 1 \end{bmatrix} * \begin{bmatrix} \phi_{11} & & \\ \phi_{21} & \phi_{22} & \\ \phi_{31} & \phi_{32} & \phi_{33} \end{bmatrix} +$$

$\Theta_\delta$ Theta-Delta matrix
{lower triangle}

$$\begin{bmatrix} 1 &&&&&&&&& \\ 0 & 1 &&&&&&&& \\ 0 & 0 & 1 &&&&&&& \\ 0 & 0 & 0 & 1 &&&&&& \\ 0 & 0 & 0 & 0 & \theta_{55} &&&&& \\ 0 & 0 & 0 & 0 & 0 & \theta_{66} &&&& \\ 0 & 0 & 0 & 0 & 0 & 0 & \theta_{77} &&& \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \theta_{88} && \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \theta_{99} & \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \theta_{10,10} \end{bmatrix}$$

A two-step test was conducted on the specified CFA model for the five fiscal years. First, the model was specified for VR clients with self-employment closure across the country. Second, clients with self-employment closure were compared across the U.S. Census Bureau's four regions. Region 1 Northeast comprises Connecticut, Maine, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, and Vermont. Region 2 Midwest comprises Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin. Region 3 South comprises Alabama, Arkansas, Delaware, District of Columbia, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, and West Virginia. Region 4 West comprises Alaska, Arizona, California, Colorado, Hawaii, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, and Wyoming (U.S. Census Bureau, 2010).

Model testing in SEM is used ". . . to determine the goodness of fit between the hypothesized model and the sample data . . . there will necessarily be a discrepancy between the two" (Byrne, 1998, p.7). Across the five fiscal years, the national CFA models were assessed on four widely recommended SEM goodness-of-fit indexes (see Arbuckle, 2009; Byrne, 1998; Hu & Bentler, 1999; Kline, 2005; McDonald & Ho, 2002). Each fit index examines a different part of a model and assigns a numerical value that is unique to the index as a measure of the goodness (or badness) of model fit.

The first model-fit index that was used to assess the CFA model was Pearson's likelihood Chi-Square or model Chi-Square $\chi^2$, which is used to test the fit between the restricted covariance matrix, representing the hypothesized (or predicted) structure of relationships among the variables, and the unrestricted sample covariance matrix, representing actual relationships among variables in the observed data (Arbuckle, 2009; Byrne, 1998). As $\chi^2$ value increases, model fit becomes worse. This statistic, however, is highly sensitive to large sample sizes (Byrne, 1998; Kline, 2005). The model $\chi^2$ degrees of freedom (*df*) is a measure of model parsimony (Arbuckle, 2009). The associated *p* value indicates whether the specified model should be rejected as a test of the null hypothesis that the model has perfect fit (Byrne, 1998; Kline, 2005).

The second model-fit index used, Comparative Fit Index (CFI) is a fit statistic that indicates the improvement in model fit of the specified model over the baseline or independence model, which assumes no population covariances among the observed variables. A CFI value of 0.90 or greater indicates a good fit (Hu & Bentler, 1999). The third model-fit index used, Root Mean Square Error of Approximation (RMSEA) measures the discrepancy between the population covariance matrix and the specified model (Byrne, 1998). A value of less than 0.05 indicates a good fit, a value of 0.05 to 0.08 indicates a reasonable fit, and a value of 0.10 or greater indicates a poor fit (Kline, 2005; McDonald & Ho, 2002). The fourth model-fit index used, Standardized Root Mean Square Residual (SRMR) measures ". . . the mean absolute correlation residual, the overall difference between the observed and predicted correlations" (Kline, 2005, p.141), with a value less than 0.10 ". . . generally considered favorable" (Kline, 2005, p.141).

In each fiscal year, the four U.S. Census Bureau Regions were compared for model fit. This evaluation involved testing the invariance of the CFA model across the four regions (see Cheung & Rensvold, 2002; Hoyle & Smith, 1994). Model invariance testing comprises a hierarchical series or steps in fixing certain model parameters to be equal across comparison groups and determining whether model fit significantly changes across those groups (Arbuckle, 2009; Cheung & Rensvold, 2002). The CFA model invariance testing across the four regions involved: (1) allowing freely estimated parameters across the four regions, (2) fixing factor loadings, (3) fixing factor covariances and variances, and (4) fixing residual variances. Each step beginning with (3) included keeping the previous step(s) in place. For example, in step 3, factor variances and covariances were fixed to be equal across the regions, and factor loadings (from step 2) were also kept fixed (e.g., the path from level of supports factor to public supports indicator is the same weight value in the Northeast, Midwest, South, and West regions). In the final step, indicator residuals were fixed and all previous steps held in place. Each step was compared with the previous step for model-fit changes using Chi-Square $\chi^2$ value ($\Delta\chi^2$) and degrees of freedom ($\Delta df$), and CFI ($\Delta$CFI) and RMSEA ($\Delta$RMSEA) fit indexes (see Arbuckle, 2009; Byrne, 1998; Cheung & Rensvold, 2002; Kline 2005; McDonald & Ho, 2002). The SRMR fit index was not used in the model invariance testing for the five fiscal years, FY 2003 to 2007, because the index was unavailable; it was only available and used in the CFA model testing at the national level.

For all statistical analyses in this dissertation study, in both HLM and SEM, the level of statistical significance, $\alpha$, (alpha) was initially set a priori at 0.01. The reason for setting this stringent alpha was the exploratory nature of these analyses, preemptively addressing possible nonnormality and attempting to minimize the inflation of Type I Error (see Keppel & Wickens, 2004; Kerlinger & Lee, 2002; Pedhazur & Schmelkin, 1991). The initial alpha level, however, needed a correction in the SEM analysis because statistical testing on the same RSA data occurred twice. Testing was first conducted on the entire CFA model across the fiscal years, and then subsequently conducted on the same data in the multi-step model invariance analysis of the four U.S. Census Regions. Thus, the corrected alpha for the model invariance testing was 0.0025, which was calculated by dividing 0.01 by 4, the number of tests in the invariance procedure.

# CHAPTER IV

# RESULTS

In this chapter, the results are reported for data screening and the HLM and SEM statistical analyses to answer the six research questions for this dissertation study.

## Data Screening

Data screening revealed that approximately one to three percent of analyzed variables of RSA data across all five fiscal years were missing data. The missing data were missing arbitrarily. The nature of the missing data was determined to be missing at random, or MAR (see Schafer & Graham, 2002). The missing values were then imputed in the PASW Statistics GradPack 17.0 for Windows (SPSS, Inc., 2009) statistical software program using the Multiple Imputation with Markov-Chain Monte Carlo iterative algorithm, a recommended imputation method for continuous and categorical variables with missing data that are MAR (Schafer & Graham, 2002).

The case summary of the four demographic predictors representing individual characteristics is presented in Table 1. Results indicated that the largest number of employment closure cases (*N*) occurred in FY 2003, with 214,982 closures, including self-employment and other employment. The smallest number of closures occurred in FY 2007, with 202,726 closures. Results indicated that the gender composition remained unchanged across the fiscal years, with 54% male and 46% female clients with case closure. Across the fiscal years, the ethnicity composition ranged from 23% to 27% of nonwhite clients and 73% to 77% white clients. The significant-disability status composition ranged from 7% to 9% of clients without a significant disability and 91% to 93% of clients with a significant disability. The educational attainment composition ranged from 57% to 61% of clients with up to a high-school level of education, and 39% to 43% of clients with post high-school level of education.

Table 1

Case Summary of Demographic Variables Representing Individual Characteristics

| Variable (%) | RSA Fiscal Years | | | | |
|---|---|---|---|---|---|
| | 2003 | 2004 | 2005 | 2006 | 2007 |
| Gender | | | | | |
| female | 46 | 46 | 46 | 46 | 46 |
| male | 54 | 54 | 54 | 54 | 54 |
| Ethnicity | | | | | |
| nonwhite | 27 | 24 | 23 | 23 | 23 |
| white | 73 | 76 | 77 | 77 | 77 |
| Significant disability | | | | | |
| no | 9 | 9 | 8 | 8 | 7 |
| yes | 91 | 91 | 92 | 92 | 93 |
| Educational attainment | | | | | |
| up to h.s. | 61 | 60 | 59 | 58 | 57 |
| post h.s. | 39 | 40 | 41 | 42 | 43 |
| Closure Totals | 214982 | 210931 | 203820 | 202977 | 202726 |

The total number of VR cases for each fiscal year is presented in Appendix A; this total includes self-employment closure, other employment closure, and no closure.

Descriptive statistics of the continuous variables are presented in Table 2 for the five fiscal years. Results indicated the mean (*M*) total number of VR services for clients ranged from 4.22 to 4.50, with a range of standard deviations (*SD*) from 2.16 to 2.25. The mean (*M*) cost of VR services ranged from $3963.08 to $4810.98, with a range of standard deviations (*SD*) from 7193.72 to 8602.21. The mean (*M*) monthly dollar amount of public supports at closure ranged from $167.26 to $201.56, with a range of standard deviations (*SD*) from 330.79 to 377.08. The mean (*M*) number of medical support services at closure ranged from 0.72 to 0.77, with a range of standard deviations (*SD*) from 0.59 to 0.60. The mean (*M*) weekly earnings at closure ranged from $305.52 to $349.10, with a range of standard deviations (*SD*) from 222.86 to 266.23. The mean (*M*) number of hours worked in a typical week at closure ranged from 31.37 to 31.77, with a range of standard deviations (*SD*) from 11.32 to 11.99. Dollar amounts were unadjusted. Thus, direct comparisons were not possible as they had not been indexed for inflation (e.g., CPI) across the five-year span, FY 2003 to 2007, in the analyses.

As indicated by their mean (*M*) and standard-deviation (*SD*) values, the three "monetary" variables of cost of VR services, weekly earnings, and public supports, and the variable of weekly hours worked showed some nonnormality in their distributions, in their skewness and kurtosis statistics. These other descriptive statistics are presented in Appendix B tables. Because the two distinct analyses, HLM and SEM, were to be conducted on the same data, stringent a priori level of significance (alpha) for statistical tests was applied to account for the effects of nonnormality and potential inflation of Type I Error. Also, the effects of any nonnormality would appear in the model results and would be addressed appropriately with further elaboration in subsequent chapters.

Table 2

Descriptive Statistics of Service, Support, and Employment Variables

| Variable | RSA Fiscal Years | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 2003 | | 2004 | | 2005 | | 2006 | | 2007 | |
| | *M* | *SD* | *M* | *SD* | *M* | *SD* | *M* | *SD* | *M* | *SD* |
| Number of VR services | 4.22 | 2.16 | 4.25 | 2.16 | 4.38 | 2.19 | 4.50 | 2.25 | 4.50 | 2.25 |
| Cost of VR services | 3963.08 | 7193.72 | 4021.22 | 7315.46 | 4403.75 | 8060.37 | 4595.97 | 8167.03 | 4810.98 | 8602.21 |
| Public supports | 167.91 | 330.79 | 167.26 | 336.51 | 177.61 | 346.89 | 190.45 | 362.90 | 201.56 | 377.08 |
| Number of medical support services | 0.72 | 0.59 | 0.73 | 0.59 | 0.74 | 0.60 | 0.76 | 0.60 | 0.77 | 0.60 |
| Weekly earnings | 305.52 | 222.86 | 312.57 | 232.26 | 322.51 | 236.10 | 336.00 | 251.38 | 349.10 | 266.23 |
| Weekly hours worked | 31.37 | 11.99 | 31.59 | 11.74 | 31.67 | 11.54 | 31.77 | 11.37 | 31.73 | 11.32 |

**Hierarchical Linear Modeling**

To answer the first three research questions, a two-level HGLM analysis was conducted. The results of this analysis are described in the following sections, organized by research question in sequential order and presented in tables, from Table 3 to Table 7 for FY 2003 to FY 2007, respectively.

*Research Question 1*. The first research question asked, “What are significant predictors of self-employment case closure for VR clients?” In FY 2003, the significant predictors ($p$<.001) of VR clients’ self-employment case closure were gender

(*B*= -0.2710, *SE*=0.0301), ethnicity (*B*=0.5889, *SE*=0.0412), cost of VR services (*B*=0.00002, *SE*=0.000001), educational attainment (*B*=0.2818, *SE*=0.0303), and public supports (*B*=0.00083, *SE*=0.00003).

In FY 2004, the significant predictors ($p<.001$) of VR clients' self-employment case closure were gender (*B*= -0.2624, *SE*=0.0310), ethnicity (*B*=0.5471, *SE*=0.0431), cost of VR services (*B*=0.00002, *SE*=0.000001), educational attainment (*B*=0.3162, *SE*=0.0312), public supports (*B*=0.0007, *SE*=0.000035), and significant disability (*B*=0.2429, *SE*=0.0586).

In FY 2005, the significant predictors ($p<.001$) of VR clients' self-employment case closure were gender (*B*= -0.2830, *SE*=0.0329), ethnicity (*B*=0.6462, *SE*=0.0479), cost of VR services (*B*=0.00002, *SE*=0.000001), educational attainment (*B*=0.3059, *SE*=0.0330), and public supports (*B*=0.0008, *SE*=0.000035).

In FY 2006, the significant predictors ($p<.001$) of VR clients' self-employment case closure were gender (*B*= -0.3017, *SE*=0.0338), ethnicity (*B*=0.6437, *SE*=0.0489), cost of VR services (*B*=0.00002, *SE*=0.000001), educational attainment (*B*=0.3004, *SE*=0.0338), and public supports (*B*=0.0008, *SE*=0.00003).

In FY 2007, the significant predictors ($p<.001$) of VR clients' self-employment case closure were gender (*B*= -0.3272, *SE*=0.0340), ethnicity (*B*=0.5422, *SE*=0.0470), cost of VR services (*B*=0.00002, *SE*=0.000001), educational attainment (*B*=0.3105, *SE*=0.0339), and public supports (*B*=0.0007, *SE*=0.00003).

The average unemployment of states (*AvgUnemp*), the lone level-2 predictor in the HGLM analysis, was not statistically significant in any fiscal year's model result.

Table 3

Statistics for 2-Level HGLM Self-Employment Closure – FY 2003

| Fixed Effect | | B | *SE* | *df* | *p* | Exp (B) | Robust *SE* |
|---|---|---|---|---|---|---|---|
| | | | | Unconditional Model | | | |
| Mean log odds intercept | $\gamma_{00}$ | -3.8247 | 0.1054 | 50 | <.001 | 0.0218 | 0.1044 |
| | | | | Conditional Model | | | |
| Mean log odds Intercept | $\gamma_{00}$ | -4.3797 | 0.1199 | 49 | <.001 | 0.0125 | 0.1720 |
| AvgUnemp | $\gamma_{01}$ | 0.0105 | 0.0994 | 49 | 0.917 | 1.0105 | 0.1012 |
| Gender | $\gamma_{10}$ | -0.2710 | 0.0301 | 214974 | <.001 | 0.7626 | 0.0322 |
| Ethnic | $\gamma_{20}$ | 0.5889 | 0.0412 | 214974 | <.001 | 1.8020 | 0.0463 |
| CostVR | $\gamma_{30}$ | 0.00002 | 0.000001 | 214974 | <.001 | 1.00002 | 0.000003 |
| EducAtt | $\gamma_{40}$ | 0.2818 | 0.0303 | 214974 | <.001 | 1.3255 | 0.0769 |
| PubSupp | $\gamma_{50}$ | 0.00083 | 0.00003 | 214974 | <.001 | 1.0008 | 0.000054 |
| SigDisab | $\gamma_{60}$ | 0.0015 | 0.0522 | 214974 | 0.978 | 1.0015 | 0.1128 |

| Random Effect | | Variance Component | $\chi^2$ | *df* | *p* |
|---|---|---|---|---|---|
| | | Unconditional Model | | | |
| State mean log odds | $u_{0j}$ | 0.5359 | 2319.05 | 50 | <.001 |
| | | Conditional Model | | | |
| State mean log odds | $u_{0j}$ | 0.5086 | 2404.81 | 49 | <.001 |

Table 4

Statistics for 2-Level HGLM Self-Employment Closure – FY 2004

| Fixed Effect | | B | *SE* | *df* | *p* | Exp (B) | Robust *SE* |
|---|---|---|---|---|---|---|---|
| | | | Unconditional Model | | | | |
| Mean log odds intercept | $\gamma_{00}$ | -3.8756 | 0.1029 | 50 | <.001 | 0.0207 | 0.1019 |
| | | | Conditional Model | | | | |
| Mean log odds Intercept | $\gamma_{00}$ | -4.6374 | 0.1237 | 49 | <.001 | 0.0097 | 0.2246 |
| AvgUnemp | $\gamma_{01}$ | -0.0031 | 0.0977 | 49 | 0.975 | 0.9969 | 0.0903 |
| Gender | $\gamma_{10}$ | -0.2624 | 0.0310 | 210923 | <.001 | 0.7692 | 0.0385 |
| Ethnic | $\gamma_{20}$ | 0.5471 | 0.0431 | 210923 | <.001 | 1.7282 | 0.0751 |
| CostVR | $\gamma_{30}$ | 0.00002 | 0.000001 | 210923 | <.001 | 1.00002 | 0.000002 |
| EducAtt | $\gamma_{40}$ | 0.3162 | 0.0312 | 210923 | <.001 | 1.3718 | 0.0901 |
| PubSupp | $\gamma_{50}$ | 0.0007 | 0.000035 | 210923 | <.001 | 1.0007 | 0.000064 |
| SigDisab | $\gamma_{60}$ | 0.2429 | 0.0586 | 210923 | <.001 | 1.2749 | 0.1360 |

| Random Effect | | Variance Component | $\chi^2$ | *df* | *p* |
|---|---|---|---|---|---|
| | | Unconditional Model | | | |
| State mean log odds | $u_{0j}$ | 0.5096 | 2530.07 | 50 | <.001 |
| | | Conditional Model | | | |
| State mean log odds | $u_{0j}$ | 0.5085 | 2738.86 | 49 | <.001 |

Table 5

Statistics for 2-Level HGLM Self-Employment Closure – FY 2005

| Fixed Effect | | B | *SE* | *df* | *p* | Exp (B) | Robust *SE* |
|---|---|---|---|---|---|---|---|
| | | | Unconditional Model | | | | |
| Mean log odds intercept | $\gamma_{00}$ | -3.9948 | 0.1128 | 50 | <.001 | 0.0184 | 0.1117 |
| | | | Conditional Model | | | | |
| Mean log odds Intercept | $\gamma_{00}$ | -4.6526 | 0.1333 | 49 | <.001 | 0.0095 | 0.2046 |
| AvgUnemp | $\gamma_{01}$ | 0.0242 | 0.1183 | 49 | 0.839 | 1.0245 | 0.1354 |
| Gender | $\gamma_{10}$ | -0.2830 | 0.0329 | 203812 | <.001 | 0.7535 | 0.0539 |
| Ethnic | $\gamma_{20}$ | 0.6462 | 0.0479 | 203812 | <.001 | 1.9082 | 0.0912 |
| CostVR | $\gamma_{30}$ | 0.00002 | 0.000001 | 203812 | <.001 | 1.00002 | 0.000003 |
| EducAtt | $\gamma_{40}$ | 0.3059 | 0.0330 | 203812 | <.001 | 1.3578 | 0.0862 |
| PubSupp | $\gamma_{50}$ | 0.0008 | 0.000035 | 203812 | <.001 | 1.0008 | 0.000052 |
| SigDisab | $\gamma_{60}$ | 0.0414 | 0.0615 | 203812 | 0.500 | 1.0423 | 0.1304 |

| Random Effect | | Variance Component | $\chi^2$ | *df* | *p* |
|---|---|---|---|---|---|
| | | Unconditional Model | | | |
| State mean log odds | $u_{0j}$ | 0.6132 | 2576.53 | 50 | <.001 |
| | | Conditional Model | | | |
| State mean log odds | $u_{0j}$ | 0.5919 | 2687.89 | 49 | <.001 |

Table 6

Statistics for 2-Level HGLM Self-Employment Closure – FY 2006

| Fixed Effect | | B | *SE* | *df* | *p* | Exp (B) | Robust *SE* |
|---|---|---|---|---|---|---|---|
| Unconditional Model | | | | | | | |
| Mean log odds intercept | $\gamma_{00}$ | -4.0714 | 0.1236 | 50 | <.001 | 0.0171 | 0.1224 |
| Conditional Model | | | | | | | |
| Mean log odds Intercept | $\gamma_{00}$ | -4.6828 | 0.1433 | 49 | <.001 | 0.0093 | 0.2343 |
| AvgUnemp | $\gamma_{01}$ | 0.0709 | 0.1222 | 49 | 0.564 | 1.0735 | 0.1316 |
| Gender | $\gamma_{10}$ | -0.3017 | 0.0338 | 202969 | <.001 | 0.7395 | 0.0442 |
| Ethnic | $\gamma_{20}$ | 0.6437 | 0.0489 | 202969 | <.001 | 1.9035 | 0.0831 |
| CostVR | $\gamma_{30}$ | 0.00002 | 0.000001 | 202969 | <.001 | 1.00002 | 0.000002 |
| EducAtt | $\gamma_{40}$ | 0.3004 | 0.0338 | 202969 | <.001 | 1.3503 | 0.0827 |
| PubSupp | $\gamma_{50}$ | 0.0008 | 0.00003 | 202969 | <.001 | 1.0008 | 0.000055 |
| SigDisab | $\gamma_{60}$ | -0.0075 | 0.0625 | 202969 | 0.904 | 0.9925 | 0.1429 |

| Random Effect | | Variance Component | $\chi^2$ | *df* | *p* |
|---|---|---|---|---|---|
| Unconditional Model | | | | | |
| State mean log odds | $u_{0j}$ | 0.7409 | 3676.90 | 50 | <.001 |
| Conditional Model | | | | | |
| State mean log odds | $u_{0j}$ | 0.7192 | 3672.80 | 49 | <.001 |

Table 7

Statistics for 2-Level HGLM Self-Employment Closure – FY 2007

| Fixed Effect | | B | *SE* | *df* | *p* | Exp (B) | Robust *SE* |
|---|---|---|---|---|---|---|---|
| | | | Unconditional Model | | | | |
| Mean log odds intercept | $\gamma_{00}$ | -4.0861 | 0.1146 | 50 | <.001 | 0.0168 | 0.1135 |
| | | | Conditional Model | | | | |
| Mean log odds Intercept | $\gamma_{00}$ | -4.6674 | 0.1376 | 49 | <.001 | 0.0094 | 0.2438 |
| AvgUnemp | $\gamma_{01}$ | 0.0146 | 0.1220 | 49 | 0.905 | 1.0148 | 0.1417 |
| Gender | $\gamma_{10}$ | -0.3272 | 0.0340 | 202718 | <.001 | 0.7210 | 0.0439 |
| Ethnic | $\gamma_{20}$ | 0.5422 | 0.0470 | 202718 | <.001 | 1.7198 | 0.0607 |
| CostVR | $\gamma_{30}$ | 0.00002 | 0.000001 | 202718 | <.001 | 1.00002 | 0.000003 |
| EducAtt | $\gamma_{40}$ | 0.3105 | 0.0339 | 202718 | <.001 | 1.3641 | 0.1031 |
| PubSupp | $\gamma_{50}$ | 0.0007 | 0.00003 | 202718 | <.001 | 1.0007 | 0.00007 |
| SigDisab | $\gamma_{60}$ | 0.0735 | 0.0638 | 202718 | 0.250 | 1.0763 | 0.1420 |

| Random Effect | | Variance Component | $\chi^2$ | *df* | *p* |
|---|---|---|---|---|---|
| | | Unconditional Model | | | |
| State mean log odds | $u_{0j}$ | 0.6322 | 3711.22 | 50 | <.001 |
| | | Conditional Model | | | |
| State mean log odds | $u_{0j}$ | 0.6368 | 3899.01 | 49 | <.001 |

*Research Question 2*. The second research question asked, "Do significant predictors of self-employment case closure for VR clients differ over time (e.g., multiple fiscal years)?" The significant predictors ($p$<.001) of self-employment closure for VR clients differed only for FY 2004, when all six level-1 predictors (gender, ethnicity, cost of VR services, educational attainment, public supports, and significant disability status) were statistically significant. In contrast, significant disability status was not statistically significant in the other fiscal years (FY 2003, FY 2005, FY 2006, and FY 2007).

*Research Question 3*. The third research question asked, "Do significant predictors of self-employment case closure for VR clients differ depending on service location?" The significant predictors of closure in self-employment for FY 2003 were the same across the states. For the educational attainment predictor, however, the estimated model-based standard error (*SE*=0.0303) and robust standard error (*SE*=0.0769) differed considerably, indicating possible significant differences in random effects among states and misspecification in the random effects distribution.

The significant predictors of self-employment closure in FY 2004 were the same across the states. The estimated model-based and robust standard errors, however, differed considerably for these predictors: ethnicity model-based (*SE*=0.0431) and robust (*SE*=0.0751); educational attainment model-based (*SE*=0.0312) and robust (*SE*=0.0901); and the significant disability status model-based (*SE*=0.0586) and robust (*SE*=0.1360) errors. In addition, for significant disability status, the estimated robust standard error resulted in a statistically nonsignificant result for the predictor. These differences between the standard errors indicated possible significant differences in random effects among states and misspecification in the random effects distribution.

The significant predictors of self-employment closure in FY 2005 were the same for across the states. The estimated model-based and robust standard errors, however, differed considerably for these predictors: gender model-based (*SE*=0.0329) and robust (SE=0.0539); ethnicity model-based (*SE*=0.0479) and robust (*SE*=0.0912); educational attainment model-based (*SE*=0.0330) and robust (*SE*=0.0862); and public supports model-based (*SE*=0.000035) and robust (*SE*=0.000052). These differences between the standard errors indicated possible significant differences in random effects among states and misspecification in the random effects distribution.

Significant predictors of self-employment closure in FY 2006 were the same across the states. The estimated model-based and robust standard errors, however, differed considerably for these predictors: gender model-based (*SE*=0.0338) and robust (*SE*=0.0442); ethnicity model-based (*SE*=0.0489) and robust (*SE*=0.0831); educational attainment model-based (*SE*=0.0338) and robust (*SE*=0.0827); and public supports model-based (*SE*=0.00003) and robust (*SE*=0.000055). These differences between the standard errors indicated possible significant differences in random effects among states and misspecification in the random effects distribution.

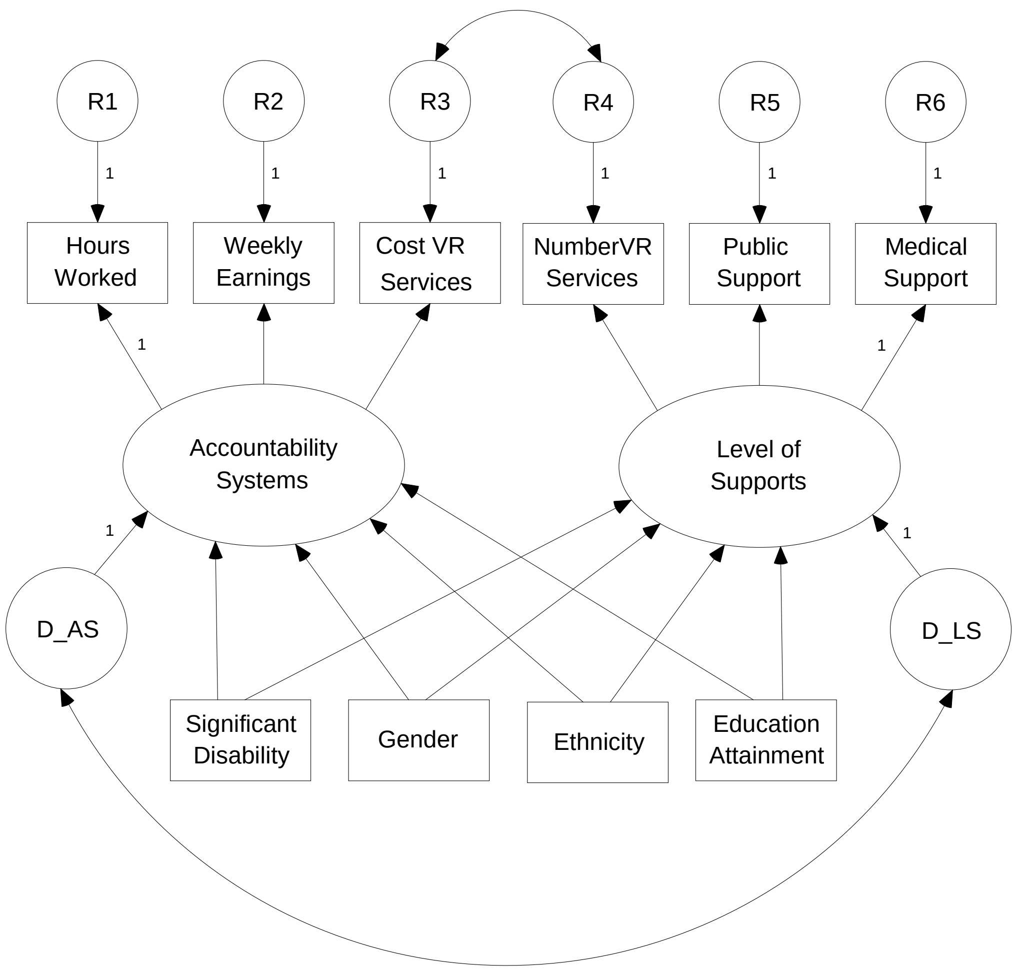
Significant predictors of self-employment closure in FY 2007 were the same across states. The estimated model-based and robust standard errors, however, differed considerably for these predictors: gender model-based (*SE*=0.0340) and robust (*SE*=0.0439); ethnicity model-based (*SE*=0.0470) and robust (*SE*=0.0607); educational attainment model-based (*SE*=0.0339) and robust (*SE*=0.1031); and public supports model-based (*SE*=0.00003) and robust (*SE*=0.00007). These differences between the standard errors indicated possible significant differences among states in random effects and misspecification in the random effects distributions.

**Structural Equation Modeling**

The specified CFA model to answer the final three research questions produced an inadmissible solution (see Arbuckle, 2008), indicating problems such as improper estimates (e.g., negative variances, correlations >1.0) or correlations of exogenous variables beyond a particular range that causes the covariance matrix to be singular or nonpositive definite (Jöreskog & Sörbom, 1984; Kline, 2005). Therefore, a model respecification was necessary (see Arbuckle, 2009; Byrne, 1998; Kline, 2005).

In the model respecification, the previously specified factors of accountability systems and level of supports, and their indicators and residuals, were retained, but the individual characteristics factor was removed. The four observed indicators of that former factor were retained and respecified as exogenous variables (previously endogenous). The four variables were respecified not to correlate and respecified with regression paths to the two factors. The two factors were respecified as both exogenous and endogenous latent variables with disturbances ($D_x$), which are residuals for endogenous variables (Byrne, 1998; Kline, 2005). The required unit-loading constraints of 1.0 were applied to the paths from disturbances to factors for scaling and identification. Disturbances were also specified to correlate, to reflect the assumption ". . . that the factors have common omitted causes" (Kline, 2005, p.308). Residuals for Cost of VR Services and the Number of VR Services (R3 and R4) indicators were specified to correlate, to reflect the assumption that cost of VR services is likely to correlate positively with the number of services. Depicted in Figure 3, this respecified model is known as a "Multiple Indicators and Multiple Causes" or MIMIC model (Kline, 2005, p.194). Model parameters were estimated in the AMOS 17.0.2 software with Maximum Likelihood (Arbuckle, 2009).

Figure 3. Respecified MIMIC Model for FY 2003 to FY 2007




*Research Question 4*. The fourth research question asked, "What is the relationship of individual characteristics, level of supports, and accountability systems to self-employment success?" The MIMIC model freely estimated 26 parameters, consisting of 8 regression paths from the exogenous categorical predictors (i.e., structural weights), 4 regression paths from factors to indicators (i.e., factor loadings), 1 covariance between

R3 and R4 residuals, 1 covariance between D_LS and D_AS disturbances, 4 variances of exogenous predictors, 2 variances of disturbances, and 6 variances of residuals. The respecified recursive model was over-identified, with 29 degrees of freedom (*df*): 55 variances and covariances were available to be estimated for 10 observed variables (10(10+1)/2), minus 26 freely-estimated parameters (see Byrne, 1998; Kline 2005).

The MIMIC model in FY 2003 ($N$=4867) converged to an admissible solution. The standardized (i.e., $X \sim N(\mu, \sigma^2)$, then $Z \sim N(0, 1)$) regression estimates that were statistically significant ($p$<.001) included paths from significant disability to accountability systems (-0.106), significant disability to level of supports (0.281), gender to accountability systems (-0.220), educational attainment to level of supports (0.206), accountability systems to hours worked (0.869), accountability systems to weekly earnings (0.582), level of supports to number of VR services (0.251), level of supports to public supports (0.652), and level of support to medical supports (0.574). The estimated correlations (i.e., standardized covariances) were significant ($p$<.001) for R3 and R4 (0.224), and for D_AS and D_LS (-0.525). The estimated variances were significant ($p$<.001) for gender (0.240), significant disability (0.087), ethnicity (0.135), educational attainment (0.249), D_AS (122.479), D_LS (0.118), R1 (42.296), R2 (61767.85), R3 (117672280.52), R4 (4.311), R5 (108229.49), and R6 (0.272).

In FY 2004, the MIMIC model ($N$=4568) converged to an admissible solution. The significant ($p$<.001) standardized regression estimates included paths from significant disability to accountability systems (-0.115), significant disability to level of supports (0.233), gender to accountability systems (-0.208), educational attainment to level of supports (0.188), accountability systems to hours worked (0.901), accountability systems to weekly earnings (0.450), level of supports to number of VR services (0.239), level of support to public supports (0.709), and level of support to medical supports (0.604). Estimated correlations were significant ($p<.001$) for R3 and R4 (0.239), and for D_AS and D_LS (-0.473). Estimated variances were significant ($p<.001$) for significant disability (0.074), gender (0.240), ethnicity (0.132), educational attainment (0.250), D_AS (136.133), D_LS (0.138), R1 (33.386), R2 (135954.20), R3 (119812651.58), R4 (4.615), R5 (96685.56), and R6 (0.264).

In FY 2005, the MIMIC model ($N$=4078) converged to an admissible solution. Significant ($p<.001$) standardized regression estimates included paths from significant disability to accountability systems (-0.124), significant disability to level of supports (0.251), gender to accountability systems (-0.184), educational attainment to level of supports (0.227), accountability systems to hours worked (0.866), accountability systems to weekly earnings (0.606), level of supports to number of VR services (0.239), level of support to public supports (0.733), and level of support to medical supports (0.617). Estimated correlations were significant ($p<.001$) for R3 and R4 (0.224), and for D_AS and D_LS (-0.469). Estimated variances were significant ($p<.001$) for significant disability (0.078), gender (0.239), ethnicity (0.118), educational attainment (0.250), D_AS (125.922), D_LS (0.147), R1 (44.228), R2 (57963.06), R3 (159356917.81), R4 (4.196), R5 (91823.28), and R6 (0.271).

In FY 2006, the MIMIC model ($N$=3903) converged to an admissible solution. Significant ($p<.001$) standardized regression estimates included paths from significant disability to accountability systems (-0.126), significant disability to level of supports (0.254), gender to accountability systems (-0.176), educational attainment to level of supports (0.197), accountability systems to hours worked (0.894), accountability systems to weekly earnings (0.530), level of supports to number of VR services (0.274), level of support to public supports (0.710), and level of support to medical supports (0.615). Estimated correlations were significant ($p$<.001) for R3 and R4 (0.276), and for D_AS and D_LS (-0.483). Estimated variances were significant ($p$<.001) for significant disability (0.078), gender (0.238), ethnicity (0.120), educational attainment (0.250), D_AS (133.825), D_LS (0.151), R1 (35.115), R2 (92486.77), R3 (107079214.75), R4 (4.338), R5 (121388.84), and R6 (0.277).

In FY 2007, the MIMIC model ($N$=3889) converged to an admissible solution. Significant ($p$<.001) standardized regression estimates included paths from significant disability to accountability systems (-0.126), significant disability to level of supports (0.237), gender to accountability systems (-0.237), educational attainment to level of supports (0.250), accountability systems to hours worked (0.941), accountability systems to weekly earnings (0.497), level of supports to number of VR services (0.280), level of support to public supports (0.681), and level of support to medical supports (0.592). Estimated correlations were significant ($p$<.001) for R3 and R4 (0.221), and for D_AS and D_LS (-0.478). Estimated variances were significant ($p$<.001) for significant disability (0.073), gender (0.237), ethnicity (0.131), educational attainment (0.250), D_AS (140.496), D_LS (0.134), R2 (138666.31), R3 (159220101.84), R4 (4.446), R5 (121554.49), and R6 (0.284); and R1 was not significant in FY 2007.

Table 8 contains the standardized estimates for the regression paths; Table 9 contains estimates for the correlations and variances. The tables are followed by the computed (not estimated) squared multiple correlations ( $R^2$ ) of endogenous variables.

Table 8

MIMIC Model Standardized Regression Path Estimates for FY 2003 to FY 2007

| Path* | FY 2003 | FY 2004 | FY 2005 | FY 2006 | FY 2007 |
|---|---|---|---|---|---|
| Sig Disab to Acct Syst | -0.106* | -0.115* | -0.124* | -0.126* | -0.126* |
| Sig Disab to Level Supp | 0.281* | 0.233* | 0.251* | 0.254* | 0.237* |
| Gender to Acct Syst | -0.220* | -0.208* | -0.184* | -0.176* | -0.237* |
| Gender to Level Supp | -0.012 | 0.000 | -0.013 | -0.028 | 0.029 |
| Ethn to Acct Syst | 0.005 | -0.005 | 0.014 | 0.006 | -0.002 |
| Ethn to Level Supp | 0.036 | 0.021 | 0.049 | 0.023 | 0.016 |
| Ed Attain to Acct Syst | -0.010 | -0.041 | -0.036 | -0.026 | -0.070 |
| Ed Attain to Level Supp | 0.206* | 0.188* | 0.227* | 0.197* | 0.250* |
| Acct Syst to Hrs Worked | 0.869* | 0.901* | 0.866* | 0.894* | 0.941* |
| Acct Syst to Wk Earnings | 0.582* | 0.450* | 0.606* | 0.530* | 0.497* |
| Acct Syst to VR Svc Cost | 0.003 | -0.006 | 0.033 | -0.005 | 0.001 |
| Level Supp to Numb VR Svc | 0.251* | 0.239* | 0.329* | 0.274* | 0.280* |
| Level Supp to Public Supp | 0.652* | 0.709* | 0.733* | 0.710* | 0.681* |
| Level Supp to Medical Supp | 0.574* | 0.604* | 0.617* | 0.615* | 0.592* |

* Significant at $p<.001$

Table 9

MIMIC Model Correlation and Variance Estimates for FY 2003 to FY 2007

| Parameter* | FY 2003 | FY 2004 | FY 2005 | FY 2006 | FY 2007 |
|---|---|---|---|---|---|
| | | | Correlations | | |
| R3 and R4 | 0.224* | 0.239* | 0.224* | 0.276* | 0.221* |
| D_AS to D_LS | -0.525* | -0.473* | -0.469* | -0.483* | -0.478* |
| | | | Variances | | |
| Sig Disab | 0.087* | 0.074* | 0.078* | 0.078* | 0.073* |
| Gender | 0.240* | 0.240* | 0.239* | 0.238* | 0.237* |
| Ethnicity | 0.135* | 0.132* | 0.118* | 0.120* | 0.131* |
| Ed Attain | 0.249* | 0.250* | 0.250* | 0.250* | 0.250* |
| D_AS | 122.479* | 136.133* | 125.922* | 133.825* | 140.496* |
| D_LS | 0.118* | 0.138* | 0.147* | 0.151* | 0.134* |
| R 1 | 42.296* | 33.386* | 44.228* | 35.115* | 19.871 |
| R 2 | 61767.85* | 135954.20* | 57963.06* | 92486.77* | 138666.31* |
| R 3 | 117672280.52* | 119812651.58* | 159356917.81* | 107079214.75* | 159220101.84* |
| R 4 | 4.311* | 4.615* | 4.196* | 4.338* | 4.446* |
| R 5 | 108229.49* | 96685.56* | 91823.28* | 121388.84* | 121554.49* |
| R 6 | 0.272* | 0.264* | 0.271* | 0.277* | 0.284* |

* Significant at $p<.001$

Squared multiple correlations ($R^2$) indicated the proportion of variance explained for endogenous variables. In FY 2003, $R^2$ values were: medical supports (0.330), public supports (0.426), weekly earnings (0.339), hours worked (0.755), cost of VR services (0.000), number of VR services (0.063), level of supports (0.123), and accountability systems (0.060). In FY 2004, $R^2$ were: medical supports (0.365), public supports (0.503), weekly earnings (0.203), hours worked (0.812), cost of VR services (0.000), number of VR services (0.057), level of supports (0.090), and accountability systems (0.058). In FY 2005, $R^2$ were: medical supports (0.381), public supports (0.537), weekly earnings (0.367), hours worked (0.750), cost of VR services (0.001), number of VR services (0.108), level of supports (0.117), and accountability systems (0.051). In FY 2006, $R^2$ were: medical supports (0.379), public supports (0.504), weekly earnings (0.281), hours worked (0.800), cost of VR services (0.000), number of VR services (0.075), level of supports (0.104), and accountability systems (0.048). In FY 2007, $R^2$ were: medical supports (0.350), public supports (0.463), weekly earnings (0.247), hours worked (0.885), cost of VR services (0.000), number of VR services (0.078), level of supports (0.120), and accountability systems (0.077). These $R^2$ values are all presented in Table 10.

Table 10

MIMIC Model Squared Multiple Correlations for FY 2003 to FY 2007

| Variable | FY 2003 | FY 2004 | FY 2005 | FY 2006 | FY 2007 |
|---|---|---|---|---|---|
| Medical Supp | 0.330 | 0.365 | 0.381 | 0.379 | 0.350 |
| Public Supp | 0.426 | 0.503 | 0.537 | 0.504 | 0.463 |
| Wk Earnings | 0.339 | 0.203 | 0.367 | 0.281 | 0.247 |
| Hrs Worked | 0.755 | 0.812 | 0.750 | 0.800 | 0.885 |
| Cost VR Svc | 0.000 | 0.000 | 0.001 | 0.000 | 0.000 |
| Numb VR Svc | 0.063 | 0.057 | 0.108 | 0.075 | 0.078 |
| Level Supp | 0.123 | 0.090 | 0.117 | 0.104 | 0.120 |
| Acct Syst | 0.060 | 0.058 | 0.051 | 0.048 | 0.077 |

*Research Question 5*. The fifth research question asked, “Does the relationship of individual characteristics, level of supports, and accountability systems to self-employment success differ over time?” In FY 2003, the MIMIC model resulted in Chi-Square $\chi^2(29)= 496.088$, $p <.001$, with CFI=0.891, RMSEA=0.058, and SRMR=0.0417. In FY 2004, the MIMIC model resulted in $\chi^2(29)=456.238$, $p <.001$, with CFI=0.884, RMSEA=0.057, and SRMR=0.0409. In FY 2005, the MIMIC model resulted in $\chi^2(29)=427.384$, $p <.001$, CFI=0.904, RMSEA=0.058, and SRMR=0.0402. In FY 2006, the MIMIC model resulted in $\chi^2(29)=480.463$, $p <.001$, with CFI=0.878, RMSEA=0.063, and SRMR=0.0455. In FY 2007, the MIMIC model resulted in $\chi^2(29)=537.189$, $p <.001$, with CFI=0.860, RMSEA=0.067, and SRMR=0.0481. The MIMIC model fit was best in FY 2005, although some misfit was present in each fiscal year as indicated by the Chi-Square and CFI values. The results of the model fit statistics for the five fiscal years are presented in Table 11.

Table 11
MIMIC Model Fit Statistics for FY 2003 to FY 2007

| Fiscal Year | $\chi^2$ | *df* | *p* | CFI | RMSEA | SRMR |
|---|---|---|---|---|---|---|
| FY 2003 (*N*=4867) | 496.088 | 29 | <.001 | 0.891 | 0.058 | 0.0417 |
| FY 2004 (*N*=4568) | 456.238 | 29 | <.001 | 0.884 | 0.057 | 0.0409 |
| FY 2005 (*N*=4078) | 427.384 | 29 | <.001 | 0.904 | 0.058 | 0.0402 |
| FY 2006 (*N*=3903) | 480.463 | 29 | <.001 | 0.878 | 0.063 | 0.0455 |
| FY 2007 (*N*=3889) | 537.189 | 29 | <.001 | 0.860 | 0.067 | 0.0481 |

*Research Question 6*. The sixth and final research question asked, “Does the relationship of individual characteristics, level of supports, and accountability systems to self-employment success differ by location?” In each fiscal year, the MIMIC model was tested for invariance across the four Census Regions, with alpha correction for six steps: 01/6 = 0.00167. In FY 2003, the first step of the invariance test, in which specified model parameters were freely estimated for the regions, resulted in $\chi^2(116)=496.622$, $p<.001$, with CFI=0.903 and RMSEA=0.026, indicating reasonable model fit. Step 2 with fixed factor loadings resulted in $\chi^2(128)=531.252$, $p<.001$, CFI=0.897, RMSEA=0.025, also indicating reasonable fit. A small difference from step 1 in CFI ($\Delta$CFI=0.006) and RMSEA ($\Delta$RMSEA=0.001) occurred, but the significant change in $\chi^2$ ($\Delta\chi^2=34.63$, $\Delta df=12$, $p<.001$) indicated that the regions significantly differed in fit (see Cheung & Rensvold, 2002). Step 3 with fixed structural weights (and holding step 2 in place) resulted in $\chi^2(152)=600.073$, $p<.001$; with CFI=0.886, and RMSEA=0.025, an increase in model misfit. A small change occurred from step 2 in CFI ($\Delta$CFI=0.011), but a significant change in $\chi^2$ ($\Delta\chi^2=68.821$, $\Delta df=24$, $p<.001$) indicated significant fit differences among regions. Step 4 with fixed factor variances and covariances (and holding steps 2 and 3 in place) resulted in $\chi^2(164)=1994.048$, $p<.001$; CFI=0.546, RMSEA=0.047, indicating poor overall model fit. Thus, further invariance testing was unnecessary (see Cheung & Rensvold, 2002). In fully reporting the testing outcomes, however, step 5 resulted in $\chi^2(173)=2000.272$, $p<.001$; CFI=0.534, RMSEA=0.047. Step 6 resulted in $\chi^2(194)=2502.452$, $p<.001$; CFI=0.411, RMSEA=0.049. The entire results of the model invariance testing for FY 2003 are presented in Table 12.

Table 12

MIMIC Model Invariance Results for FY 2003

| Invariance Comparison | $\chi^2$ | *df* | *p* | CFI | RMSEA |
|---|---|---|---|---|---|
| National Model | 496.088 | 29 | <.001 | 0.891 | 0.058 |
| Regional four-group model | | | | | |
| 1. All parameters freely estimated | 496.622 | 116 | <.001 | 0.903 | 0.026 |
| 2. Fixed factor loadings | 531.252 | 128 | <.001 | 0.897 | 0.025 |
| 3. Fixed structural weights and #2 | 600.073 | 152 | <.001 | 0.886 | 0.025 |
| 4. Fixed factor variances and covariances and #3 | 1994.048 | 164 | <.001 | 0.546 | 0.047 |
| 5. Fixed disturbances and #4 | 2000.272 | 173 | <.001 | 0.534 | 0.047 |
| 6. Fixed residuals and #5 (fixed all parameters) | 2502.452 | 194 | <.001 | 0.411 | 0.049 |

In FY 2004, the first step of the invariance test resulted in $\chi^2$ (116)=505.124, $p$<.001, CFI=0.892, RMSEA=0.027, indicating reasonable model fit. Step 2 results were $\chi^2$ (128)=567.595, $p$<.001; CFI=0.879, RMSEA=0.027, indicating some model misfit. A small change from step 1 in CFI ($\Delta$CFI=0.013) occurred, but a significant change in $\chi^2$ ($\Delta\chi^2$=62.471, $\Delta df$=12, $p$<.001) indicated that the regions had become significantly different from each other in model fit (see Cheung & Rensvold, 2002). Step 3 results were $\chi^2$ (152)=603.472, $p$<.001; CFI=0.875, RMSEA=0.026, indicating an increasing model misfit. A small change occurred from step 2 in CFI ($\Delta$CFI=0.004) and RMSEA ($\Delta$RMSEA=0.001) and some change in $\chi^2$ ($\Delta\chi^2$=35.877, $\Delta df$ =24) indicated no significant change in fit from the previous step. Step 4 results were $\chi^2$ (164)=1714.407, *p*<.001, and CFI=0.571, RMSEA=0.046, indicating poor overall model fit. With an increase in RMSEA and a significantly larger $\chi^2$ and low CFI (much less than the recommended 0.90 or greater value), indicating poor overall model fit, further invariance testing across the regions was unnecessary (see Cheung & Rensvold, 2002). In fully reporting invariance test outcomes, however, step 5 ($\chi^2$ (173)=1754.553, *p*<.001; CFI=0.563, RMSEA=0.045) and step 6 ($\chi^2$ (194)=3487.376, *p*<.001; CFI=0.090, RMSEA=0.061) indicated very poor overall fit. The entire results of the model invariance testing for FY 2004 are presented in Table 13.

Table 13
MIMIC Model Invariance Results for FY 2004

| Invariance Comparison | $\chi^2$ | *df* | *p* | CFI | RMSEA |
|---|---|---|---|---|---|
| National Model | 456.238 | 29 | <.001 | 0.884 | 0.057 |
| Regional four-group model | | | | | |
| 1. All parameters freely estimated | 505.124 | 116 | <.001 | 0.892 | 0.027 |
| 2. Fixed factor loadings | 567.595 | 128 | <.001 | 0.879 | 0.027 |
| 3. Fixed structural weights and #2 | 603.472 | 152 | <.001 | 0.875 | 0.026 |
| 4. Fixed factor variances and covariances and #3 | 1714.407 | 164 | <.001 | 0.571 | 0.046 |
| 5. Fixed disturbances and #4 | 1754.553 | 173 | <.001 | 0.563 | 0.045 |
| 6. Fixed residuals and #5 (fixed all parameters) | 3487.376 | 194 | <.001 | 0.090 | 0.061 |

In FY 2005, the first step of the invariance test resulted in $\chi^2$ (116)=473.506, $p$<.001, CFI=0.908, RMSEA=0.028, indicating reasonable model fit. Step 2 results were $\chi^2$ (128)=560.039, $p$<.001, with CFI=0.888 and RMSEA=0.029, indicating some model misfit. A small change from step 1 in CFI ($\Delta$CFI=0.02) and RMSEA ($\Delta$RMSEA=0.001) occurred, but a significant change in $\chi^2$ ($\Delta\chi^2$=86.533, $\Delta df$=12, $p$<.001) indicated that the regions had become significantly different from each other in model fit (see Cheung & Rensvold, 2002). Step 3 results were $\chi^2$ (152)=594.766, $p$<.001, with CFI=0.886 and RMSEA=0.027, indicating an increasing model misfit. A small change occurred from step 2 in CFI ($\Delta$CFI=0.002) and RMSEA ($\Delta$RMSEA=0.002) and some change in $\chi^2$ ($\Delta\chi^2$=34.727, $\Delta df$ =24) indicated no significant change in fit from the previous step. Step 4 results were $\chi^2$ (164)=1399.947, $p$<.001, with CFI=0.681 and RMSEA=0.043, indicating poor overall model fit. With an increase in RMSEA and a significantly larger $\chi^2$ and low CFI (much less than the recommended 0.90 or greater value), indicating poor overall model fit, further invariance testing across the regions was unnecessary (see Cheung & Rensvold, 2002). In fully reporting the model invariance testing outcomes, however, step 5 resulted in $\chi^2$ (173)=1427.958, $p$<.001, with CFI=0.676 and RMSEA=0.042. Step 6 resulted in $\chi^2$ (194)=2424.109, $p$<.001, with CFI=0.424 and RMSEA=0.053. The results of both step 5 and step 6 of the invariance test indicated very poor overall model fit across all four regions. This was first indicated by the poor model fit at step 4. The entire results of the model invariance testing across the four U.S. Census regions for FY 2005 are presented in Table 14.

Table 14

MIMIC Model Invariance Results for FY 2005

| Invariance Comparison | $\chi^2$ | *df* | *p* | CFI | RMSEA |
|---|---|---|---|---|---|
| National Model | 427.384 | 29 | <.001 | 0.904 | 0.058 |
| Regional four-group model | | | | | |
| 1. All parameters freely estimated | 473.506 | 116 | <.001 | 0.908 | 0.028 |
| 2. Fixed factor loadings | 560.039 | 128 | <.001 | 0.888 | 0.029 |
| 3. Fixed structural weights and #2 | 594.766 | 152 | <.001 | 0.886 | 0.027 |
| 4. Fixed factor variances and covariances and #3 | 1399.947 | 164 | <.001 | 0.681 | 0.043 |
| 5. Fixed disturbances and #4 | 1427.958 | 173 | <.001 | 0.676 | 0.042 |
| 6. Fixed residuals and #5 (fixed all parameters) | 2424.109 | 194 | <.001 | 0.424 | 0.053 |

In FY 2006, the first step of the invariance test resulted in $\chi^2$ (116)=530.201, $p$<.001, CFI=0.883, RMSEA=0.030, indicating some model misfit. Step 2 results were $\chi^2$ (128)=571.477, $p$<.001, with CFI=0.875 and RMSEA=0.030, indicating further model misfit. A small change from step 1 in CFI ($\Delta$CFI=0.008) occurred, but a significant change in $\chi^2$ ($\Delta\chi^2$=41.276, $\Delta df$=12, $p$<.001) indicated that the regions had become significantly different from each other in model fit (see Cheung & Rensvold, 2002). Step 3 results were $\chi^2$ (152)=609.398, $p$<.001, CFI=0.871 and RMSEA=0.028, indicating an increasing model misfit. A small change occurred from step 2 in CFI ($\Delta$CFI=0.004) and RMSEA ($\Delta$RMSEA=0.002) and some change in $\chi^2$ ($\Delta\chi^2$=37.921, $\Delta df$ =24) indicated no significant change in model fit from the previous step. Step 4 results were $\chi^2$ (164)=1717.144, $p$<.001, with CFI=0.562 and RMSEA=0.049, indicating poor overall model fit. With an increase in RMSEA and a significantly larger $\chi^2$ and low CFI (much less than the recommended 0.90 or greater value), indicating poor overall model fit, further invariance testing was unnecessary (see Cheung & Rensvold, 2002). In fully reporting the MIMIC model invariance testing outcomes, however, step 5 results were $\chi^2$ (173)=1759.490, $p$<.001, with CFI=0.553 and RMSEA=0.048. Step 6 results were $\chi^2$ (194)=2930.857, $p$<.001, with CFI=0.228 and RMSEA=0.060. Results of step 5 and step 6 of the invariance test indicated very poor overall model fit across all four regions. This was first indicated by the poor model fit at step 4. The entire results of the model invariance testing for FY 2006 are presented in Table 15.

Table 15

MIMIC Model Invariance Results for FY 2006

| Invariance Comparison | $\chi^2$ | *df* | *p* | CFI | RMSEA |
|---|---|---|---|---|---|
| National Model | 480.463 | 29 | <.001 | 0.878 | 0.063 |
| Regional four-group model | | | | | |
| 1. All parameters freely estimated | 530.201 | 116 | <.001 | 0.883 | 0.030 |
| 2. Fixed factor loadings | 571.477 | 128 | <.001 | 0.875 | 0.030 |
| 3. Fixed structural weights and #2 | 609.398 | 152 | <.001 | 0.871 | 0.028 |
| 4. Fixed factor variances and covariances and #3 | 1717.144 | 164 | <.001 | 0.562 | 0.049 |
| 5. Fixed disturbances and #4 | 1759.490 | 173 | <.001 | 0.553 | 0.048 |
| 6. Fixed residuals and #5 (fixed all parameters) | 2930.857 | 194 | <.001 | 0.228 | 0.060 |

In FY 2007, the first step of the invariance test resulted in $\chi^2$ (116)=626.552, $p$<.001, CFI=0.859, RMSEA=0.034, already indicating some model misfit. Step 2 results were $\chi^2$ (128)=712.755, $p$<.001, with CFI=0.839 and RMSEA=0.034, indicating further model misfit. A small change from step 1 in CFI ($\Delta$CFI=0.020) occurred, but the significant change in $\chi^2$ ($\Delta\chi^2$=86.203, $\Delta df$=12, $p$<.001) indicated that the regions had become significantly different from each other in model fit (see Cheung & Rensvold, 2002). Step 3 results were $\chi^2$ (152)=742.755, $p$<.001, CFI=0.837 and RMSEA=0.032, indicating an increasing model misfit. A small change occurred from step 2 in CFI ($\Delta$CFI=0.002) and RMSEA ($\Delta$RMSEA=0.002), and some change in $\chi^2$ ($\Delta\chi^2$=30.00, $\Delta df$ =24) indicated no significant change in model fit from the previous step. Step 4 results were $\chi^2$ (164)=2135.369, $p$<.001, with CFI=0.456 and RMSEA=0.056, which indicated very poor overall model fit across the regions. With an increase in RMSEA and a significantly larger $\chi^2$ and low CFI (much less than the recommended 0.90 or greater value), indicating very poor overall model fit, further invariance testing was unnecessary (see Cheung & Rensvold, 2002). In fully reporting the invariance testing outcomes, however, step 5 results were $\chi^2$ (173)=2160.473, $p$<.001, with CFI=0.452 and RMSEA=0.054. Step 6 results were $\chi^2$ (194)=2960.214, $p$<.001, with CFI=0.237 and RMSEA=0.061. The results of both step 5 and step 6 of the model invariance testing indicated very poor overall fit across all regions, which was first indicated in step 4. The entire results of the model invariance testing for FY 2007 are presented in Table 16.

Table 16

MIMIC Model Invariance Results for FY 2007

| Invariance Comparison | $\chi^2$ | *df* | *p* | CFI | RMSEA |
|---|---|---|---|---|---|
| National Model | 537.189 | 29 | <.001 | 0.860 | 0.067 |
| Regional four-group model | | | | | |
| 1. All parameters freely estimated | 626.552 | 116 | <.001 | 0.859 | 0.034 |
| 2. Fixed factor loadings | 712.755 | 128 | <.001 | 0.839 | 0.034 |
| 3. Fixed structural weights and #2 | 742.755 | 152 | <.001 | 0.837 | 0.032 |
| 4. Fixed factor variances and covariances and #3 | 2135.269 | 164 | <.001 | 0.456 | 0.056 |
| 5. Fixed disturbances and #4 | 2160.473 | 173 | <.001 | 0.452 | 0.054 |
| 6. Fixed residuals and #5 (fixed all parameters) | 2960.214 | 194 | <.001 | 0.237 | 0.061 |

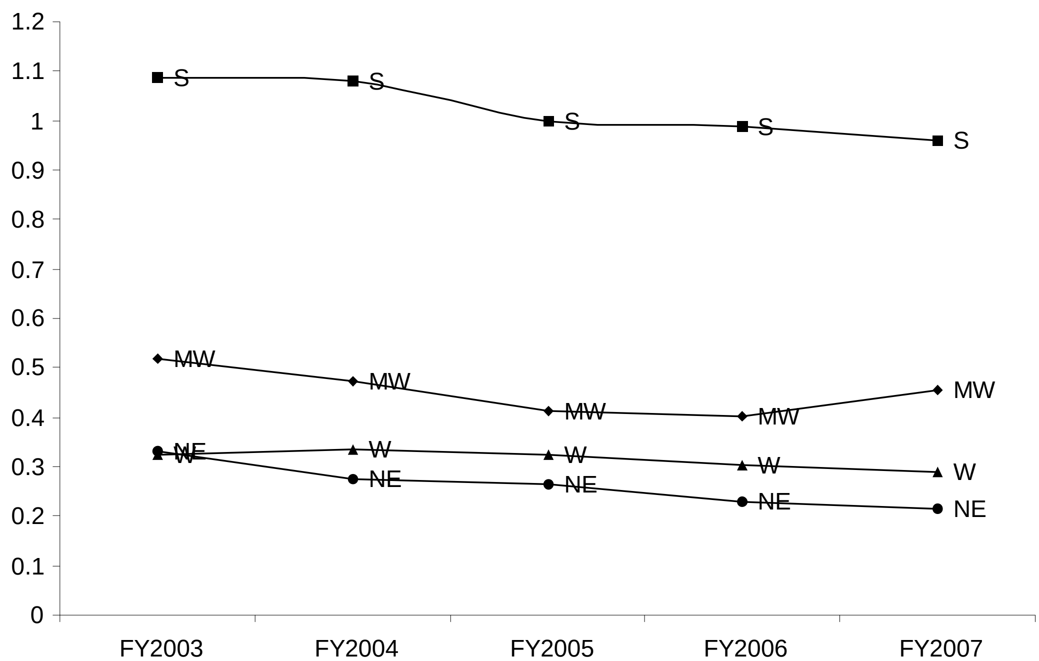
The national (*N*) and regional sample sizes (*n*) for each fiscal year are presented in Table 17. The largest group of VR case closures in self-employment over the five fiscal years occurred in FY 2003, with 4867 closures; the smallest occurred in FY 2007, with 3889 closures. The U.S. Census Region with the largest number of self-employment closures from FY 2003 to FY 2007 was Region 3 South, with the largest regional number of self-employment closures occurring in FY 2003 (*n*=2339), at least twice the number of any other region. Also, Region 3 South maintained the highest self-employment closure rates across the fiscal years, with the highest rates occurring in FY 2003 (1.09%) and FY 2004 (1.08%). This rate is based on the number of self-employment closures out of the total number of VR closures for all employment outcomes in a fiscal year (see Table 1). These closure rates are displayed in Figure 4 by Census region (NE, MW, S, and W).

Table 17

MIMIC Model National and Regional Sample Sizes for FY 2003 to FY 2007

| Sample | FY 2003 | FY 2004 | FY 2005 | FY 2006 | FY 2007 |
|---|---|---|---|---|---|
| Total N | 4867 | 4568 | 4078 | 3903 | 3889 |
| Region 1 Northeast (NE) | 714 | 583 | 539 | 463 | 433 |
| Region 2 Midwest (MW) | 1116 | 1001 | 845 | 820 | 921 |
| Region 3 South (S) | 2339 | 2280 | 2035 | 2004 | 1947 |
| Region 4 West (W) | 698 | 704 | 659 | 616 | 588 |

Figure 4. VR Self-Employment FY Closure Rate (%) by U.S. Census Region



CHAPTER V

DISCUSSION

In this chapter, the results of the HLM and SEM statistical analyses are interpreted, the limitations of the analyses are outlined, and the implications for various stakeholder groups are discussed in turn.

**Hierarchical Linear Modeling**

*Research Question 1*. This question asked, "What are the significant predictors of self-employment case closure for VR clients?" A two-step process in HGLM was utilized to analyze the RSA data for each fiscal year, first by specifying an unconditional model to analyze the outcome variable without predictors, followed by a conditional model in which predictors were specified. For the unconditional models across the five fiscal years, the estimated log odds, $\hat{\gamma}_{00}$, which are all statistically significant ($p$<.001), range in value from -4.0861 to -3.8247. This is an indication that closures are significantly more likely for other employment (coded as 0) than for self-employment (coded as 1) in every state. The estimated variance in the mean log odds of states, $\hat{\tau}_{00}$, range from 0.5096 to 0.7409, are all significant ($p$<.001), indicating significant differences among states.

In Table 3 to Table 7, Exp(B) is the Odds Ratio, which are the relative odds converted from log odds by $e^{B}$, where $e$ is the Euler value of approximately 2.7182818 and exponent $B$ is the log-odds regression coefficient. Among unconditional models, the highest odds ratio of self-employment closure, 0.0218 (95% CI, 0.018 to 0.027), is computed for FY 2003. Thus, for a state with a "typical" self-employment closure rate, a random effect $u_{0j}$ value of 0, the expected odds of self-employment is 0.0218, which does not include the effects of predictors. That is, for every self-employment closure, approximately fifty closures would occur in other employment (1/50=0.02). The 95% confidence interval of 0.018 and 0.027 also indicates that the proportion of intervals from many (theoretically infinite) repeated trials of this analysis that includes an odds ratio of 0.0218 will be approximately 95 percent. Finally, the measure of over-dispersion and under-dispersion of level-1 variance, scalar variance component $\hat{\sigma}^2$, ranges in value from 0.98 to 0.99, which is very close to 1.00, indicating that neither problematic dispersion condition is likely to be present (Raudenbush et al., 2002).

The conditional models provide estimates of the log odds of self-employment closure of VR clients across states affected by six predictors at level-1 and one predictor at level-2 for each of the five fiscal years (see Table 3 to Table 7). The estimated log odds of self-employment, $\hat{\gamma}_{00}$, ranging in value from -4.6828 to -4.3797, are statistically significant ($p$<.001). This is the estimated log odds of self-employment closure for a male, nonwhite VR client who received his state's average cost of VR services, whose educational attainment at closure was no more than a high-school level, who received his state's average dollar amount of public supports at closure, who identified as not having a significant disability, and lived in a state with a $u_{0j}$ value of 0. His probability of closure in self-employment in FY 2003 is 1/(1+ ExpB{4.3797}) = 0.0124, or 1.24%. The log odds also indicate VR clients are significantly more likely to achieve closure in other employment than in self-employment. The estimated mean variance of the log odds, $\hat{\tau}_{00}$, ranging from 0.5086 to 0.7192, are all significant ($p$<.001), indicating significant differences among states. This finding is consistent with a recent analysis by Revell et al. (2009), who found that several states, Mississippi, Wyoming, Alaska, and Maine, have had consistently higher rates of self-employment case closure than the other states.

Among the significant predictors ($p$<.001) of self-employment closure across the fiscal years, the strongest effects are found, in order of strength, for ethnicity, educational attainment, and gender. Ethnicity is associated with higher log odds of self-employment closure, holding constant other predictors and the random effect, $u_{0j}$. The estimated regression coefficient values of ethnicity, $\hat{\gamma}_{20}$, representing the mean fixed slopes (i.e., unique effect of ethnicity fixed across states) range from 0.5422 to 0.6462. The largest ethnicity slope is 0.6462 in FY 2005, where a unit increase in ethnicity of VR clients (from 0 nonwhite to 1 white) increases the log odds of self-employment closure by 0.6462. The corresponding odds ratio is 1.9082 (95% CI, 1.737, 2.096). White clients have nearly a 91-percent increase in their odds over nonwhite clients. The expected odds of self-employment closure for white clients are nearly double the expected odds for nonwhite clients. Under the assumption of a null hypothesis, the significant $p$<.001 value indicates that in fewer than 1 in 1000 cases an odds ratio of self-employment closure this large will occur for nonwhite clients.

Educational attainment is associated with higher log odds of self-employment closure, holding constant other predictors and the random effect, $u_{0j}$. The estimated regression coefficient values of educational attainment, $\hat{\gamma}_{40}$, representing the mean fixed slopes, range from 0.2818 to 0.3162 across the fiscal years. The largest mean educational attainment slope is 0.3162 in FY 2004, where a unit increase in the predictor (from 0 up to high school to 1 post-high school) increases the log odds of self-employment closure by 0.3162. The corresponding odds ratio is 1.3718 (95% CI, 1.290, 1.458), indicating that the expected odds of self-employment closure for clients with a post-high school level of education are 1.37 times the expected odds for clients with up to (but no more than) a high school level of education. Thus, the odds of self-employment closure increase by approximately 37 percent for clients with post-high school education. A strong link between VR self-employment closure and post-high school education is also documented in the empirical research literature (e.g.., Blanck et al., 2000).

Gender is associated with lower log odds of self-employment closure, holding constant other predictors and the random effect, $u_{0j}$. The estimated regression coefficient values of gender, $\hat{\gamma}_{10}$, representing the mean fixed slopes, range from -0.3272 to -0.2624. The largest gender slope is -0.2624 in FY 2004, where a unit increase in gender (from 0 male to 1 female) decreases the log odds of self-employment closure by 0.2624. The corresponding odds ratio is 0.7692 (95% CI, 0.724, 0.817), indicating that the expected odds of self-employment closure for female VR clients are 0.7692 times the expected odds for male clients. Thus, the odds of self-employment closure decrease by nearly 23 percent for females. Conversely, an increase of 0.2624 in the log odds for male clients corresponds to an odds ratio of 1.3000, or a 30-percent increase in odds for males.

The remaining significant predictors are the "monetary" variables, cost of VR services and public supports. While these predictors cannot be compared directly across the fiscal years because the dollar values are not adjusted for inflation, their effect on the log odds of self-employment closure can be interpreted. Cost of VR services is associated with higher log odds of self-employment closure, holding constant other predictors and the random effect, $u_{0j}$. Estimated regression coefficients of the predictor, $\hat{\gamma}_{30}$, represent the mean fixed slopes. In FY 2003, for example, the coefficient of 0.00002 is the increase in the log odds of self-employment closure associated with a unit increase in the cost of VR services. The corresponding odds ratio is 1.00002. That is, if two VR clients are similar in the other ways but differ by one unit on the cost of VR services they received, the odds of self-employment closure for the client with the higher cost of VR services is expected to be 1.00002 times the odds of the client with the lower cost of VR services. In perspective, the standard deviation of this predictor variable (see Table 1) in FY 2003 is 7193.72. Therefore, one standard deviation difference in the cost of VR services is associated with a change in the log odds of 7193.72 * (0.00002) = 0.1439, which corresponds to an odds ratio of 1.1548, or 15 percent increase in odds.

Public supports associate with higher log odds of self-employment closure, holding constant the other predictors and the random effect, $u_{0j}$. Estimated regression coefficients of public supports, $\hat{\gamma}_{50}$, represent the mean fixed slopes. In FY 2003, for example, the coefficient of 0.00083 is the increase of log odds associated with a unit increase in public supports (dollars) received by clients. The corresponding odds ratio is 1.0008. That is, if two VR clients are similar in the other ways but differ by one unit on the dollar amount of public supports they received, the odds of self-employment closure for the client with the higher amount of public supports is expected to be 1.0008 times the odds of the client with the lower amount of public supports. These effects are <u>nonlinear</u>. As an example, the aforementioned typical VR client in FY 2003 with a unit increase in public supports would have an expected log odds of -4.3797 + 0.0008 = -4.3789, which corresponds to an odds ratio of 0.012539 and a predicted probability of 1/(1+ Exp(B) of 4.3789) = 0.012384, or 1.23% . An additional unit increase in public supports would result in a predicted log odds of -4.3797 + (0.0008 + 0.0008) = -4.3781 with an odds ratio of 0.012549 and a predicted probability of 1/(1+Exp(B) of 4.3781) = 0.012394; these probabilities are not additive however (e.g., 0.012384 + 0.012384 = 0.024768).

The results of the HGLM analysis for Research Question 1 reveal that while individual characteristics place some VR clients ahead of others in their likelihood of case closure in self-employment ("success" in VR) and that white male clients with a post-high school level of education are most likely to achieve VR self-employment closure, clients still are significantly more likely to achieve case closure in other employment. Case closure in self-employment is just a very rare occurrence overall within VR, between 2% and 3% nationally since the late 1980s (Ipsen, Arnold, & Colling, 2005; Schriner & Neath, 1996). The very low rate of VR self-employment closure, which has remained stably – perhaps remarkably – over many years, could be explained by bureaucratic inertia or other factors within the VR system, in light of the higher rates of self-employment for individuals with disabilities outside the VR system (see President's Committee on Employment of People with Disabilities, 2000).

*Research Question 2*. This question asked, "Do significant predictors of self-employment case closure for VR clients differ over time?" As first noted in the previous chapter (Chapter IV: Results) about the differences between model-based standard errors and robust standard errors, the only problematic result occurs for the significant disability status predictor in FY 2004, where using the model-based standard error ($SE$=0.0586) produces a significant ($p$<.001) result, but using the robust standard error ($SE$=0.1360) produces a nonsignificant result. Because this predictor is not significant in any other fiscal year, caution must be taken in interpreting the model-based result. The nonsignificant result is likely the correct interpretation. In analyzing differences between model-based and robust standard errors, Raudenbush and Bryk (2002) note "Large discrepancies typically signal model misspecification" (p.278). While the other significant predictors also have some differences between their model-based and robust standard errors, their statistical test results remain significant ($p$<.001). The fact that significant effects of ethnicity, gender, educational attainment, cost of VR services, and public supports on the likelihood of self-employment closure remain consistent over multiple years is noteworthy, and suggests that while an empirical trend analysis has not been conducted, at the very least, a model trend could be considered.

*Research Question 3*. This question asked, “Do significant predictors of self-employment case closure for VR clients differ depending on service location?” Significant predictors of self-employment case closure for VR clients do not differ across states. In addition, the $\beta_{0j}$ (log odds) state-level intercepts across the fiscal years, in the unconditional and conditional models, range from .94 to .95, indicating a high degree of reliability of estimates of these intercepts. Reliability is based on the precision of estimation of a regression equation for each state and how much variability of the “true underlying parameters” (Raudenbush & Bryk, 2002, p.79) occurs across states. The precision in estimating $\beta_{0j}$ intercepts is dependent on sample size within each state (Raudenbush & Bryk, 2002). As noted previously, each RSA fiscal year data contains more than 200,000 cases of VR employment closures. The parameter-estimate solutions across all the fiscal years in the unconditional and conditional models also were all reached within eight macro iterations, a relatively rapid solution. The quick convergence to solutions suggests that these model parameters are not difficult to estimate. These results are not suggesting, however, that a state-by-state variation in the slopes (i.e., random effects of predictors which were not tested) is not occurring. In fact, the misspecification may be one indication of this variability – and the need to test these random effects. Certainly, some states, such as New Mexico, Hawaii, and California, are more ethnically heterogeneous in their population than other states, and the strength of the ethnicity effect on self-employment closure could vary significantly across states. These differences, in terms of the odds-ratios for white and nonwhite clients, could mean that in a more homogenous state, the odds of self-employment closure for white clients over nonwhite clients are significantly greater than in a more heterogeneous state.

**Structural Equation Modeling**

*Research Question 4*. This question asked, “What is the relationship of individual characteristics, level of supports, and accountability systems to self-employment success?” The initial specified CFA model resulted in an inadmissible solution, which then necessitated respecification based on theory rather than by empirical methods based on the data (e.g., use of Modification Indices). This approach is used to avoid capitalizing on chance, which reduces the generalizability of findings (MacCallum, Roznowksi, & Necowitz, 1992). The respecified SEM model, known as a MIMIC model, tested the assumption that, for VR clients with self-employment closure in a given fiscal year, the differences in specific individual characteristics of gender, ethnicity, educational attainment, and significant disability status would directly predict the two factors, level of supports and accountability systems, which then would explain variances of their indicators and residuals, the latter accounting for what is left unexplained by the model.

The MIMIC model produced an admissible solution for each fiscal year. The model fit reasonably well in FY 2003 to FY 2005, with indications of some misfit. The model fit less well in FY 2006 and FY 2007, with more model misfit according to the four model-fit indexes used: Chi-Square (degrees of freedom and p-value), CFI, RMSEA, and SRMR. McDonald and Ho (2002) assert, “The presence of categorical variables or indicators may cause nonnormality,” (p.70) but also assert “. . . ML estimation and its associated statistics seem fairly robust against nonnormality” (p.70). This suggests that the overall MIMIC model misfit is less likely explained by the presence of the gender, ethnicity, educational attainment, and significant disability variables or the nonnormality among the “monetary” variables (weekly earnings, cost of VR services, and public supports) and more likely to be found in some misspecification of the model itself. While the model has captured some aspect of the relationship of individual characteristics, level of supports, and accountability systems to self-employment success through VR, it also has left some of that relationship unexplained. This means that specifying different or additional indicators and different factor structure is warranted (guided by theory) and is likely to produce a MIMIC model with better fit to the RSA data.

*Research Question 5*. This question asked, “Does the relationship of individual characteristics, level of supports, and accountability systems to self-employment success differ over time?” Notably across all five fiscal years, the same regression paths are significant ($p$<.001). For the exogenous variables predicting the two factors, the paths (known as structural weights) from significant disability to accountability systems range from -0.106 to -0.126, and the paths from significant disability to level of supports range from 0.233 to 0.281. These coefficients represent measurements of predictors’ direct effects on the factors. Thus, among VR clients with self-employment closure, those without a significant disability are significantly more likely to predict accountability systems, and those with a significant disability are significantly more likely to predict level of supports. One explanation for these findings is that (a) clients without a significant disability are more likely to work longer hours and have different intrinsic or extrinsic motivation related to a number of potential gains from self-employment (see Chapter II: Literature Review), and (b) VR services and public supports are more likely to accrue for clients with a significant disability due to higher level of support needs directly related to their disability condition and self-employment work requirements.

The path from gender to accountability systems ranges from -0.176 to -0.237. Thus, male clients (coded as 0) are significantly more likely to predict accountability systems. An explanation of this result is that male clients are working more hours and have higher average weekly earnings than female clients. Also, the path from educational attainment to level of supports ranges from 0.188 to 0.250. Thus, clients with post-high school education are significantly more likely than clients with up-to-high school level of education to predict level of supports. A possible explanation of this result is that clients with post-high school education have more information and awareness of services and supports and will be more likely to self-advocate for those needs in self-employment.

Interestingly, ethnicity has no significant effect on accountability systems or level of supports: white and nonwhite clients do not differ significantly in predicting either factor. Because the MIMIC model includes only clients with self-employment closure, this nonsignificant finding suggests that, perhaps, ethnicity is more directly and significantly predictive of the quality – not the amount or level – of supports, and more predictive of other business-related factors that are not included here, beyond the three variables of accountability systems that were analyzed in the MIMIC model.

For the two exogenous factors predicting the endogenous observed variables (i.e., factor loadings or measurement weights), the paths from accountability systems to hours worked range from 0.866 to 0.941, accountability systems to weekly earnings range from 0.450 to 0.606, and accountability systems to cost of VR services range from -0.006 to 0.033. Two of the three indicators for the accountability systems factor are substantial, significant direct effects in which the "causes" of the observed endogenous variables, hours worked and weekly earnings, are well explained in the model. The direct effect on the third indicator, cost of VR services, however, is miniscule (nearly zero); that the cost of VR services has almost no relationship with weekly earnings or hours worked. The paths from level of supports to number of VR services range from 0.239 to 0.329, level of supports to public supports range from 0.652 to 0.733, and level of supports to medical supports range from 0.574 to 0.617. All three indicators are significant; these variables have some relationship to each other. Public supports and medical supports also have moderately high factor loadings, meaning that they are capturing important facets of accountability systems. Having all high indicator loadings for a factor represents strong evidence of convergent validity (Byrne, 1998; Kline, 2005). Such evidence, though, is lacking here as the number of VR services variable has moderately low loadings.

The correlations are significant ($p$<.001) for the same variables across the fiscal years. The correlation between R3 and R4, the residual terms for the cost of VR services and the number of VR services variables respectively, range from 0.221 to 0.276. This correlation represents the assumed relationship between the two indicator variables. The correlation between D_AS and D_LS, the disturbance terms for accountability systems and level of supports respectively, range from -0.525 to -0.469. The substantial negative correlation, indicating a strong inverse relationship, suggests the presence of common but unanalyzed sources that "caused" these factors (see Kline, 2005), which are external to the model. These sources remain unexplained and as yet undefined, but nevertheless impose a certain degree of detectable significant influence on the two factors.

The variances are significant ($p$<.001) for the same variables across the fiscal years. Among the exogenous predictors, variances for significant disability range from 0.073 to 0.087, variances for gender range from 0.237 to 0.240, variances for ethnicity range from 0.118 to 0.135, and variances for educational attainment range from 0.249 to 0.250. Among the disturbances, the variances for D_AS (accountability systems factor) range from 122.479 to 140.496, and the variances for D_LS (level of supports factor) range from 0.118 to 0.151. Because these disturbances serve as factor residual terms, the large variances indicate that much more of the variance of the accountability systems factor is unexplained by the model. In addition, the four exogenous predictors account for much more of the explained variance ( $R^2$ ) for the level of supports factor, even after the correlation of the disturbance terms is taken into account.

Variances are significant ($p$<.001) for the same residuals across the fiscal years, with one exception. The R1 variance (residual for hours worked) in FY 2007 (19.871) is not significant. The variances for R1 range from 19.871 to 44.228. The variances for R2 (residual for weekly earnings) range from 57963.06 to 138666.31. The variances for R3 (residual for cost of VR services) range from 107079214.75 to 159356917.81. The variances for R4 (residual for number of VR services) range from 4.196 to 4.615. The variances for R5 (residual for public supports) range from 91823.28 to 121554.49. The variances for R6 (residual for medical supports) range from 0.264 to 0.284. These large residual variances are indicating that the MIMIC model has a significant amount of unexplained variance – a strong indication of some model misfit and misspecification.

The squared multiple correlations ( $R^2$ ) represent the variances explained for the endogenous variables in the model, the factors and their indicators. The explained variances for the two factors, level of supports (9% to 12%) and accountability systems (5% to 8%), are somewhat small. Among the indicator variables, substantial variance is explained in the model for medical supports (33% to 38%), public supports (43% to 54%), weekly earnings (20% to 37%), and hours worked (75% to 88%). Conversely, very little variance is explained for cost of VR services (between zero and one-tenth of 1%) or number of VR services; and both residual terms (R3 and R4) are correlated – a significant ($p$<.001) but not substantial correlation. Thus, among clients with self-employment closure, the effect of VR services in cost and number is nearly undetectable, unlike the effects of the non-VR variables, which are well explained in the model. Another interesting aspect of these results is that despite large residual variances for weekly earnings (R2) and public supports (R5), their $R^2$ explained variances are also significant ($p$<.001) and substantial. This result is likely another indication and potential location of model misspecification that was first indicated by the four model-fit indexes.

*Research Question 6*. This question asked, “Does the relationship of individual characteristics, level of supports, and accountability systems to self-employment success differ by location?” From FY 2003 to FY 2007, the invariance testing of the MIMIC model across the four U.S. Census Regions indicates that the model only has reasonable fit when the entire national data of self-employment closures are examined, as these data are averaged across all four regions. The significant ($p$<.001) worsening in model fit begins after the second step of testing in which the factor loadings are fixed to be equal across regions. Clearly, the regions significantly vary in the relationships among indicators of the same factor and their loadings on the factor. Also for each fiscal year, model fit becomes very poor at step 4, in which factor variances and covariances of level of supports and accountability systems are fixed to be equal across regions. This is very strong evidence that the MIMIC model fails to establish model invariance across the four regions for VR clients with case closure in self-employment; and strong evidence for both significant regional effects on the MIMIC model and some model misspecification.

The MIMIC model results suggest the misfit in FY 2006 and FY 2007 is related to sample-size differences among regions. For example, the number of self-employment closures for Region 3 South in FY 2006 (*n*=2004) is more than double the number of Region 2 Midwest (*n*=820), more than triple the number of Region 4 West (*n*=616), and more than quadruple the number of Region 1 Northeast (*n*=463). Other state-specific effects are present, but they are only indirectly measured as residual variances or as unanalyzed (i.e., external) sources of model variation. In FY 2003, the self-employment closure rate of 1.08% (2339/214982) in the South is slightly less than half of the overall national rate of 2.26% (4867/214982). In each fiscal year, the rate differences between the South and the other regions are larger than the rate differences among the other three regions (see Figure 4). The fact that such substantial regional differences have remained rather consistent over time, as have the significant effects of certain predictors on the likelihood of self-employment closure (HLM analysis), could be explained by a number of regional economic, cultural, and political factors that differentially affect VR and clients. While self-employment closure in VR remains a rare occurrence relative to other employment closures, VR in the South may be exercising more autonomy and flexibility in clients’ employment cases that are driven by a confluence of these factors.

### Limitations of this Dissertation Study

Pertaining to the first three research questions, some model misspecification in the HGLM analysis may be present, suggested by differences in the model-based and robust standard errors for some predictors across the fiscal years. Although only one of the predictors, significant disability status, was significantly affected, additional predictors at level-1 and level-2 are probably needed for improving model fit, such as age or SES or other state-level economic covariates. Additional random effects at level-2, such as those for ethnicity and educational attainment, also could be used. In this dissertation study, only the intercept (log odds of self-employment closure) was specified to randomly vary across states; the analysis was guided by a priori research questions.

Pertaining to the final three research questions, the initial CFA model did not converge to an admissible solution. The respecified MIMIC model did converge to an admissible solution, but some model misfit was indicated, more in FY 2006 and FY 2007. The MIMIC model invariance testing across the four U.S. Census Bureau regions in each fiscal year indicated that the model fit worsened significantly when the factor loadings (i.e., Lambda matrix) in step 2 and factor variances and covariances (i.e., Phi matrix) in step 4 were fixed to be equal across the regions. In addition, the issue of sample size may be especially relevant for the MIMIC invariance testing of the regions, where the Northeast and the West regions consistently had much smaller samples of VR clients with self-employment case closure than the South region did in all five fiscal years. The Maximum Likelihood estimation that is used to estimate model parameters for SEM analyses in the AMOS 17.0.2 software (used in this dissertation study) is robust against nonnormality (McDonald & Ho, 2002), but works best in producing efficient and unbiased estimators for large samples (Kline, 2005; Tabachnick & Fidell, 2007). The sample sizes of the West and Northeast regions probably would not qualify as "large."

Using mathematical transformation to correct the nonnormality in the data of the "monetary" variables was not done because it would have changed the variables' metric unit (Kline, 2005; Raudenbush and Bryk, 2002; Tabachnick & Fidell, 2007). For example, if a Log Base 10 transformation had been used on the data for the Cost of VR Services variable, the metric unit would have become "Log 10 dollars." Such a change would have been problematic in the interpretations of the model results. While the nonnormality probably did not affect the HLM analysis, it may have contributed to the model misfit in the SEM analysis, specifically, in the MIMIC model invariance testing.

The final limitation of this dissertation study is the limited number of years of data that were analyzed. The HLM and SEM analyses only included five fiscal years, FY 2003 to FY 2007. Moreover, the RSA data were constrained by the limited number and types of variables that constituted individual characteristics, level of supports, and accountability systems for the conceptual framework of this dissertation study. More important is that significant economic changes have occurred in the U.S. (and globally) since 2007, most notably a major recession. Therefore, conclusions drawn from this dissertation study may serve more appropriately as context against which economic and population changes affecting self-employment of clients through VR agencies across the U.S. are compared and understood in subsequent analyses of RSA data.

**Implications of this Dissertation Study**

This dissertation study has implications for several stakeholder groups, including researchers, VR, policy makers, and school professionals.

*Implications for researchers*. Unique in terms of its analytic approach and scope, with more than a million cases analyzed across five fiscal years with HLM and SEM statistical techniques, this dissertation study reveals the importance of conducting regular analysis of the RSA data. Because these data are in effect an annual “census” of VR services in the U.S., analyzing that data to understand self-employment and its correlates at client and state levels and across regions for multiple years constitutes empirical replications and cross validations. Researchers then can use those analyses to develop and test theories about self-employment of individuals with disabilities through VR.

*Implications for vocational rehabilitation*. The results of the analyses in this dissertation study appear to confirm disparities among groups found in other empirical research studies on self-employment (see Chapter II: Literature Review). Historically, individuals with disabilities have had difficulty gaining access to capital and loans for self-employment through conventional means, such as venture capital firms or commercial banks. These difficulties are similar to those that have been faced by women and ethnic minorities (President’s Committee on Employment of People with Disabilities, 2000). This knowledge could be used by VR in its training of counselors and in reviewing agency policies for supporting certain clients in self-employment.

Another important implication of this dissertation study for VR counselors and administrators is the use of RSA data to assess resource allocation, given the persistent fiscal challenges for state VR agencies across the country. For example, knowing the amount of resources that are used to support clients in self-employment for a given year, or how state support differs over time, could provide an empirical basis for counselors and administrators to plan ahead specific approaches or strategies. Also, the fact that certain regions and states have had consistently higher self-employment closure rates may prompt counselors or administrators to more closely examine why and how those rates are occurring, and determine whether their own policies should change.

*Implications for policy makers*. As indicated in the Literature Review (see Chapter II) and the statistical analyses of the RSA data in this dissertation study, the rates of VR self-employment case closure and their predictors have remained consistent. Perhaps not surprisingly, self-employment rates for individuals with disabilities have been higher outside the VR system (President's Committee on Employment of People with Disabilities, 2000). This leads to a counterfactual argument, which is to provide opportunities outside the VR system and then measure their differences based on sustainable long-term outcomes and cost/benefit analyses. In addition to its role through the Small Business Development Centers, government policy makers also could expand self-employment opportunities for individuals, for example, by establishing public and private partnerships with financial institutions that incubate or build start-ups, modeled after the microfinance development programs in the field of international development (Griffin & Hammis, 2008; Schriner & Neath, 1996). This model typically entails financiers establishing funds that provide small loans to businesses with five or fewer employees (Griffin & Hammis, 2008; Schriner & Neath, 1996; Walls, Dowler, Cordingly, Orslene, & Greer, 2001). The evaluations of these programs have described success not only in terms of poverty alleviation, development of business and technical skills, and self-sufficiency, but also in terms of self-determination, self-worth, and a sense of community (Lewis, 2004; Niekerk, Lorenzo, & Mdlokolo, 2006; Schreiner, 1999).

*Implications for school professionals*. School professionals can play a major role in preparing students with disabilities to explore self-employment as a possible option in adult life. Considering that the likelihood of self-employment success increases with post-high school education, as indicated by the results of this dissertation study and by other empirical studies (see Chapter II: Literature Review), the importance of school professionals is manifest. Students' required transition plan in their Individualized Education Program (IEP) should include provisions to develop entrepreneurial and business skills through coursework and experiential opportunities, such as internships or mentorships similar to the "Partners for Youth with Disabilities – Young Entrepreneurs Project" in Boston (Snowden, 2003). School professionals should also prepare students for post-high school education and training to further develop necessary skills. Active collaboration between school professionals and the business community is essential, and concrete planning among students, families, and school professionals must be a priority.

**Recommendations for Further Research**

In the last twenty years, only a small number (*n*=12) of U.S. empirical research studies have been conducted on self-employment of individuals with disabilities. The fact that the studies are empirical but nonexperimental and largely descriptive suggests research challenges ahead but also many opportunities, given the inchoate state of the literature. Further examination of self-employment will need to include international comparisons, while reconciling cultural and legal distinctions or contradistinctions.

This dissertation study leaves a number of compelling areas yet to be explored. In a subsequent analysis of the RSA data, for example, HGLM could include the effect of age. Client age was provided only for the FY 2003. Also, the interaction effects of ethnicity, gender, educational attainment, and disability status on self-employment closure could be examined, recognizing that some states have more heterogeneous populations (e.g., Hawaii, California) than other states (e.g., Wyoming, Idaho). To reduce potential bias of level-1 estimates, particularly with respect to the variable of ethnicity and educational attainment, models could also include the random effect of ethnicity ($u_{2j}$) at level-2, or a level-2 predictor to model the variability of different ethnicity compositions of states, and the random effect ($u_{4j}$) of educational attainment, or level-2 predictor to model the variability of educational attainment composition across states. What is also always important to keep in mind when analyzing these models, however, is the parsimony principle: "Given two different models with similar explanatory power for the same data, the simpler model is preferred" (Kline, 2005, p.137).

Surprisingly, in the HGLM analysis, the yearly average state unemployment rate, *AvgUnemp*, was not significant as a level-2 predictor of log odds of self-employment closure in any of the five fiscal years. Perhaps, then, in a subsequent analysis of the RSA data, a different level-2 predictor could be tested, representing a state's cost of living or another variable that is also related to a client's decision to become self-employed, such as the types of industries in a state. One of the questions to answer is whether, as some analysts have suggested, ". . . flows into self-employment occurs during recessions and flows out of self-employment occurs during economic expansions (e.g., Rissman, 2003, as cited in Hipple, 2004, p.14). One caveat in regard to adding variables in HGLM is that with a level-2 sample size of 51 (number of states and D.C.), the number of analyzed predictors and random effects have to be limited in order to produce a stable solution that converges after a reasonable number of iterations with reasonably unbiased and efficient estimators (Raudenbush & Bryk, 2002). Again, model parsimony should be considered.

In a subsequent HGLM analysis, another type of estimation of model parameters could be used, known as the "Laplace approximation of maximum likelihood" (Raudenbush et al., 2004) that utilizes the Expectation Maximization (EM) algorithm. Raudenbush et al. (2004) find that Laplace estimation ". . . produces a remarkably accurate approximation to maximum likelihood (ML) of all parameters" (p.109). That HGLM analysis, then, can be compared to the one from this dissertation study.

In a subsequent analysis of the RSA data with SEM, models could be specified with correlated residuals, or different indicators or structural effects, for example, removing the cost of VR services indicator or adding a separate factor for VR effects. For the MIMIC models in FY 2003 to 2007, the Modification Indices reveals that certain changes would significantly empirically improve model fit. Such changes that are based on data-driven empirical specification searches (akin to data fishing/mining), however, would not be theoretically defensible or scientifically sound. Researchers caution the use of such an approach because model changes would capitalize on chance, and instead, recommend changes guided by substantive theory to ensure model generalizability and replicability (MacCallum et al., 1992). Modification Indices from this dissertation study could be used to derive theories, which then could be tested on RSA data for future fiscal years (see MacCallum et al., 1992). Equivalent models, which were not examined in this dissertation study, also should be examined. These are alternative models that do not differ in fit from the original model, but are ". . . represented by different relationships among the variables" (MacCallum, Wegener, Uchino, and Fabrigar, 1993, p.185), which change interpretations and meaning of the model structure (MacCallum et al., 1993). Finally, a subsequent analysis could specify and test formative indicators for the two model factors, accountability systems and level of supports, instead of reflective indicators, which was done in this dissertation. Formative indicators are specified as “causes” of a factor, which becomes a composite latent variable with path arrows pointing to the factor, not as “effects” with arrows pointing to indicators (Kline, 2005).

Further analysis of the RSA data with SEM in Amos 17.0.2 (Arbuckle, 2008) could use Bayesian estimation, an alternative to Maximum Likelihood estimation. Bayesian estimation involves a process in which a prior distribution of a model’s parameters and the observed data are combined by Bayes Theorem to produce a posterior (updated) distribution of parameters, which are used as final results (point estimates) and compared to the observed data for assessing model fit (Arbuckle, 2009). Bayesian estimation considers “true” model parameter values as unknown and random with a joint probability distribution, whereas Maximum Likelihood estimation considers these values as unknown but fixed (Arbuckle, 2009). Comparing results of separate RSA data analyses using Bayesian and Maximum Likelihood estimation methods will be informative.

Future empirical research studies should examine the impact of new technology on self-employment of individuals with disabilities. This focus is particularly relevant given the expansion of e-commerce or online commerce (e.g., hosted turnkey) for selling a range of products and services. For example, an empirical study could examine the relationship between accessibility and usability of internet technology and outcomes in self-employment; and compare across different types of businesses and with traditional wage/salary jobs, which are also being reshaped by technological innovations. The new social-networking media are revolutionizing niche and peer-to-peer marketing, and could render self-employment as a catalyst for expanding employment opportunities and improving socioeconomic outcomes of individuals with disabilities.

Moving forward, self-employment ought to be examined empirically as a developmental process in longitudinal studies. As indicated by the conceptual framework and implied by the results of this dissertation study, self-employment is a complex developmental process that cannot be captured adequately and analyzed by empirical research in the timeframe of a typical VR employment case, which is approximately 90 days of employment leading to case closure. Such a short timeframe is unlikely to reveal significant findings for long-term self-employment success, or the complex experiences related to self-employment, for example, clients' business development, perseverance, resilience, and adaptability to changing national and international economies or specific market conditions. Conceptualizing self-employment as a developmental process places the emphasis on long-term and evolving individual and business outcomes over time as core indicators of success. Research evaluation of the Iowa EWD program (Blanck et al., 2000) is an example of an empirical longitudinal study with qualitative and quantitative data collection that examined the complexities of self-employment. An accumulation of such studies will improve our understanding of factors for sustaining self-employment success beyond the VR case period. A further major step will be to test (pre/post) the effects and measure the magnitude of the effects of a program or an intervention. Eventually, with a substantial number of such studies, meta-analyses can be conducted to derive broader theoretical explanations. Regardless of complexity, all of these empirical studies should strive to accumulate valid and reliable evidence through rigorous and systematic design, data collection, and analysis (Shadish, Cook, & Campbell, 2002).

While first of its kind, this dissertation study is by no means conclusive. It involved statistical analyses of national VR data for five recent fiscal years, but no causal inferences should be drawn. Moreover, as Gelman (2007) notes, "All models are wrong, and the purpose of model checking (as we understand it) is not to reject a model but rather to understand the ways in which it does not fit the data" (p.349). This dissertation study sought statistical models to explain VR client and state effects on self-employment. Although compelling results were found, this study is not advocating self-employment for individuals with disabilities through VR agencies as a superior employment alternative in every situation without regard to need or avocation. The contributions of this study to the extant literature emphasize the linking of empirical research to continual improvement in practice and policy for self-employment of individuals with disabilities through state VR agencies across regions and the entire country.

Self-employment of individuals with disabilities through VR agencies across the U.S. is still a rare occurrence compared to other types of employment. Yet, it is one particularly powerful way for individuals with disabilities to experience personal and emotional fulfillment, enhanced self-determination, self-esteem, and self-efficacy, and accrue financial benefits. Self-employment can also spur communities to foster broader inclusivity and fuller participation, which will result in the increased social integration of individuals with disabilities and individuals without disabilities – a greater social benefit.

APPENDIX A

CASE STATUS OF VR CLIENTS

Table A

Case Status of VR Clients

| Case Status (n) | FY 2003 | FY 2004 | FY 2005 | FY 2006 | FY 2007 |
|---|---|---|---|---|---|
| Self-employment closure | 4867 | 4586 | 4078 | 3903 | 3889 |
| Other employment closure | 210115 | 206345 | 199742 | 199074 | 198837 |
| No employment closure | 429012 | 436665 | 405681 | 406390 | 389696 |
| Total Cases (N) | 643994 | 647596 | 609501 | 609367 | 592422 |

APPENDIX B

ADDITIONAL DESCRIPTIVE STATISTICS

Table B1

*Additional Descriptive Statistics – FY 2003*

| Variable | Minimum | Maximum | Skewness | Kurtosis |
|---|---|---|---|---|
| Number of VR services | 0 | 22 | 0.981 | 1.852 |
| Cost of VR services | 0 | 604973 | 10.143 | 352.955 |
| Public supports | 0 | 10567 | 2.594 | 15.714 |
| Number of medical support services | 0 | 5 | 0.311 | 0.412 |
| Weekly earnings | 0 | 8139 | 3.029 | 32.337 |
| Weekly hours worked | 0 | 99 | -0.978 | 0.490 |

Table B2

*Additional Descriptive Statistics – FY 2004*

| Variable | Minimum | Maximum | Skewness | Kurtosis |
|---|---|---|---|---|
| Number of VR services | 1 | 22 | 0.918 | 1.445 |
| Cost of VR services | 0 | 431796 | 8.990 | 188.086 |
| Public supports | 0 | 9999 | 2.683 | 16.659 |
| Number of medical support services | 0 | 5 | 0.366 | 0.697 |
| Weekly earnings | 0 | 9999 | 3.809 | 62.163 |
| Weekly hours worked | 0 | 99 | -0.935 | 0.495 |

Table B3

*Additional Descriptive Statistics – FY 2005*

| Variable | Minimum | Maximum | Skewness | Kurtosis |
|---|---|---|---|---|
| Number of VR services | 1 | 22 | 0.890 | 1.360 |
| Cost of VR services | 0 | 620229 | 11.552 | 399.036 |
| Public supports | 0 | 9999 | 2.393 | 10.133 |
| Number of medical support services | 0 | 5 | 0.368 | 0.695 |
| Weekly earnings | 0 | 6250 | 2.705 | 19.925 |
| Weekly hours worked | 0 | 99 | -0.908 | 0.471 |

Table B4

*Additional Descriptive Statistics – FY 2006*

| Variable | Minimum | Maximum | Skewness | Kurtosis |
|---|---|---|---|---|
| Number of VR services | 1 | 22 | 0.839 | 1.156 |
| Cost of VR services | 0 | 442284 | 9.179 | 196.478 |
| Public supports | 0 | 8672 | 2.286 | 8.152 |
| Number of medical support services | 0 | 5 | 0.317 | 0.565 |
| Weekly earnings | 0 | 9999 | 3.302 | 40.262 |
| Weekly hours worked | 0 | 99 | -0.861 | 0.454 |

Table B5

*Additional Descriptive Statistics – FY 2007*

| Variable | Minimum | Maximum | Skewness | Kurtosis |
|---|---|---|---|---|
| Number of VR services | 1 | 22 | 0.851 | 1.279 |
| Cost of VR services | 0 | 416299 | 8.984 | 176.050 |
| Public supports | 0 | 5956 | 2.210 | 6.774 |
| Number of medical support services | 0 | 5 | 0.293 | 0.474 |
| Weekly earnings | 0 | 9999 | 3.813 | 52.800 |
| Weekly hours worked | 0 | 99 | -0.838 | 0.445 |

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