Essays on Disability and Employment

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A dissertation submitted to the faculty of the University of North Carolina at Chapel Hill in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Department of Economics.

Chapel Hill
2010

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Abstract

DENISE WHALEN: Essays on Disability and Employment.
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Despite the growing prevalence of disability among prime age men and strong correlations between disability and negative employment outcomes, few economic analyses address the avenues through which disability may influence these observed outcomes. Particularly, the impact of disability on employment decisions of disabled workers who remain employed is unknown. In this research, I focus on employment transitions and occupational choice, and the role these employment outcomes play as contributors to disability status and the observed difference in wages of working age males. Based on a dynamic framework of employment transitions and disability over time, the empirical model estimates equations for employer and occupational changes, occupational choice, disability status, and wages of men. The analyses are conducted using longitudinal data on individuals from the Survey of Income and Program Participation and data on occupations from the Dictionary of Occupational Titles. A nonlinear random effects joint estimation technique accounts for both permanent and time-varying unobserved heterogeneity that may influence employment transitions, wages, and disability. The results suggest that moderately disabled workers are 23 percent more likely to change occupations and/or employers compared to non-disabled men and that these transitions contribute negatively to wages through reductions in tenure. Furthermore, disabled individuals are found to select into occupations with low requirements of most job characteristics, most significantly reasoning and math. While the majority of these job characteristics have only a small impact on disability status, they have a large and significant effect on wages. The importance of controlling for occupational choice is also revealed, as the marginal effect of characteristics on wages differs across analyses that do and do not control for endogenous occupation selection.

Acknowledgments

The completion of my dissertation reflects support from many important people in my life. First in foremost, I would like to thank my advisor, Donna Gilleskie, for the countless hours spent mentoring, brainstorming, and editing on my behalf. I always knew that I could depend on Donna as both an expert economist and an emotional supporter. Donna motivated me to do my best work, and the example that she has set in her own career will always be something I aspire to.

My committee members have also been an immense help throughout the process of writing my dissertation. Thank you, David Guilkey, for teaching me not only the majority of my econometric skills, but also to enjoy econometrics. To Brian McManus, thank you for being one of the most constructive people in my graduate career. Everything I have done that you have been a part of has been improved based on your suggestions. Also, thank you to Rachel Willis, for teaching me that disabled individuals are more than just statistics, and providing a world of insight that only a true expert can. Finally, thank you to Stephen Lich-Tyler. You have assisted me not only in becoming a better researcher, but also to become a better teacher.

My family and friends have been the pillars in my life. Thank you to Mom, Dad, and Matt. You are the people that I have worked the hardest to please, but the ones who love me regardless of my achievements. Thank you for always being there for me. Also, thank you to Mike, Laura, and Beth. My time in Chapel Hill would not have been the same with out you.

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Chapter 1

Introduction

"Disabled Americans are an economically disadvantaged group. They work less, earn less, and earn lower wages when they do work."

- DeLeire (2000)

The number of people in the United States with a disability has been steadily increasing over the past several decades. This upward trend has elicited much concern over the welfare of the elderly and near elderly, and has generated interest among economists in the effect of disability on medical care consumption and retirement decisions. However, comparatively little is understood about the employment patterns and wages of prime age disabled workers despite the increasing frequency of disability among this group. In 2006, the U.S. Census Bureau reported that almost 13 percent of men aged 21-64 were disabled.[1] Furthermore, the Social Security Administration has found that a 20 year old worker has a 30 percent chance of becoming disabled before reaching retirement age.[2] Supporting this notion, a 2004 study by Lakdawalla et al. using National Health Interview Study data from 1984-2000 found that disability reports among the elderly have actually fallen while reports of those under age 50 have increased. The authors note that this trend is especially prevalent among those aged 30-49.

Disability is an important concern in the realm of economics as it is negatively correlated

[1]US Census Bureau, 2006 ACS. Data available at: http://www.census.gov/hhes/www/disability/2006acs.html

[2]Social Security Administration Disability planner. http://www.ssa.gov/dibplan/index.htm

with employment and wage outcomes. It has been well documented that persons with a disability receive lower wages, earning 16 to 18 percent less than non-disabled workers (Baldwin and Johnson, 2000; DeLeire, 2001). The combination of low employment and low wages may help explain why over 20 percent of the disabled live in poverty compared to less than 8 percent of those without a disability.[3] In order to assist this group, many social programs have been created and in 2006 over 91 billion dollars was spent on Social Security Disability Insurance payments alone.[4] These payments are only available to the disabled who do not participate in substantial gainful activity. Many other federal programs such as Ticket to Work, an incentive program for employers to hire disabled workers, are also only available to disabled individuals who are not gainfully employed. However, many disabled individuals are capable of working and continue to work following the onset of a disability.

While historically the majority of legislation regarding disability has focused on supporting disabled workers who are unable to work, the 1990 Americans with Disabilities Act (ADA) enacted laws to protect disabled workers. The ADA is an important civil rights act that prohibits discrimination in the hiring, firing, pay, and promotion of qualified disabled individuals.[5] Additionally, the act requires firms of 15 or more employees to provide "reasonable accommodations" to disabled workers. These accommodations may include flexible work hours, equipment, assistants, and other such work modifications that do not impose undue hardship on the employer. Thus, a goal of the ADA was to limit job turnover among disabled workers. However, not all employers are required to make or capable of making all accommodations requested by disabled workers and many more may not provide a welcoming atmosphere to a disabled employee. Furthermore, certain health limitations may render the individual incapable of performing required job tasks, necessitating an exit from the occupation. Therefore, even in the post-ADA era, disabled workers may still have a high rate of job turnover.

This research adds to the current literature on disability by estimating two different models

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[3] US Census Bureau, 2006 ACS. Data available at: http://www.census.gov/hhes/www/disability/2006acs.html

[4] SSA Annuals Statistical Supplement: http://www.ssa.gov/policy/docs/statcomps/supplement/2007/highlights.html

[5] For more information on the Americans with Disabilities Act, refer to www.ada.gov.

of disability and employment outcomes for men ages 25 to 60, where the second model builds upon the first. The first model is a dynamic model of employer and occupational change, wages, and disability status. Using the 1996 panel of the Survey of Income and Program Participation (SIPP), the direct impact of disability on employment transitions and the indirect impact of disability on wages through tenure is analyzed. As tenure is valuable to employers, if disabled workers change employers or occupations frequently, it may be reflected in lower wages. Since employment transitions are endogenous, modeling employer and occupational change produces unbiased estimates of the impact of tenure on wages. The second model analyzes occupational choice and disability using the SIPP and Dictionary of Occupational Titles (DOT). The DOT provides an objective measure of occupational characteristics, which are used as a basis for occupational choice among workers. Controlling for endogenous selection into an occupation, I then estimate the effect that these characteristics have on disability status. Although disabilities may occur independent of employment, there is a strong link between work and health, and this research attempts to specifically identify several of the pathways through which this relationship occurs.

In conducting estimation, one must be aware of individual variables that are unobserved by the researcher that my affect both self-reported disability status and employment outcomes. To control for this unobserved heterogeneity, correlation across the associated error terms in all equations is allowed. The equations are simultaneously estimated using a dynamic nonlinear random effects joint estimation technique that accounts for both permanent and time-varying unobserved heterogeneity.

Estimates from this analysis suggest that in a given four-month period a moderately disabled worker is 2.5 percentage points (or 23 percent) more likely to change occupations and/or employers than a non-disabled worker. These changes are found to have a significant negative impact on the wage rate of a moderately disabled worker. Disabled workers are also found to select into certain occupations, namely those that have low requirements of most occupational characteristics. Many of these characteristics effect disability. For example, working with inanimate objects (referred to in the DOT and in this paper as "things") and language are found to decrease the probability of a moderate disability and working with data increases the likelihood of a moderate limitation. Occupational characteristics are also found to have a significant effect on hourly wages.

The remainder of the dissertation is organized as follows. Chapter two reviews the measure of disability and previous literature related to the proposed research. Chapter three lays out the conceptual framework. Chapter four describes the empirical model and the random effects technique used to control for unobserved individual heterogeneity. The next chapter describes the Survey of Income and Program Participation and Dictionary of Occupational Titles, the data used in the analysis. Chapter six presents and discusses the results, and chapter seven concludes.

Chapter 2

Background

2.1 Disability

Measurement of disability has been a question underlying disability research for many years. It is commonly acknowledged that disability and health are distinct, although perhaps correlated, measures but the appropriate definition of disability is still under debate. A common measure of disability is some variation of a self-report of a work limitation. This definition is supported by the notion that only an individual can truly gauge his own ability to work, but brings up issues regarding the subjectivity of the measure. Other objective measures such as difficulty with activities of daily living (ADLs) and specific health conditions have also been cited as important indicators of disability status, but perhaps miss the relationship between health and work. In the following subsection I discuss the measure of disability I use in this research as well as alternative definitions.

The measure of disability available in the Survey of Income and Program Participation (SIPP) is based on the response to the question of whether a person has "a physical, mental, or other health condition that limits the kind or amount of work" he can perform. This measure is often referred to as a work limiting disability and is the only disability definition provided in many data sets. The definition is very similar to the definition of disability used by the Americans with Disabilities Act which defines an individual with a disability as a person who "has a physical or mental impairment that substantially limits one or more major life activities; has a record of such an impairment; or is regarded as having such an impairment."

Several studies have found the self-reported measure of disability to be superior to other indicators of disability. It has been noted that objective measures such as specific health conditions and medical reports measure health and not the capacity to work. The use of such objective measures may lead to bias in estimating the impact of disability on employment (Bound, 1991). Furthermore, using objective measures to instrument self-reports may create more bias than when self-reports alone are used (Bound, 1991). Several researchers have concluded that self-reported disability is an accurate reflection of ability to work and empirical analyses using such a measure produce unbiased results of the impact of disability on employment (Stern, 1989; Dwyer and Mitchell, 1999; Benitez-Silva et al., 2004).

Many other researchers, however, have concluded that self-reported disability is correlated with unobservables that also impact employment decisions (Anderson and Burkhauser, 1985; Bazzoli, 1985; Kerkhofs and Lindeboom, 1995; Kreider, 1999). Specifically, several potential problems have been raised with the measure. One issue, known as the justification hypothesis, is that an individual may report having a disability to justify his exit from the labor force or other labor market decisions. Thus, measures of the effect of disability on employment status, for example, would be overstated. Furthermore, disability partially determines receipt of compensation from several government programs such as Social Security Disability Insurance and Worker's Compensation. The desire to receive these types of assistance may induce individuals to report that they are disabled. A competing effect is the stigma that one might feel with classifying himself as having a disability. This stigma would cause individuals to underreport disability. Finally, even if workers are not justifying non-employment or hiding their disabilities, the question itself is subjective and thus leads to measurement error. Interpretation of disability and ability to work may differ across individuals. See Bound (1991) for a comprehensive review and comparison of self-reported measures to objective measures.

In this dissertation research I allow self-reported disability to be determined by unobservables that may be correlated with other outcomes of interest such as employment and wages. I model permanent and time-varying unobserved factors influencing disability status and employment outcomes using a flexible random effects maximum likelihood estimation known as the Discrete Factor Random Effects method. A detailed description of this approach is presented in Section 4.2.

2.2 Disability Legislation

Although there are many pieces of legislation regarding disabled individuals, and even more policies that affect a disproportionate percentage of the disabled population, in this section I focus on five pieces of disability legislation. The Social Security Disabilities Act and Supplemental Security Act are both safety net programs that help many disabled individuals who are unable to work. The Ticket to Work Program aims to return disabled individuals to work. The Americans with Disabilities Act and Individuals with Disabilities Education Act are designed to increase opportunities for disabled individuals in the workplace and in gaining education.

Social Security Disability Insurance

Social Security Disability Insurance (SSDI) is the largest Federal program that provides assistance to disabled individuals. Administered by the Social Security Administration (SSA) and passed in 1956, this safety net program provides cash assistance to people with disabilities that render them unable to work. A person is considered disabled if he has a physical or mental condition that prevents him from engaging in any substantial gainful activity and the condition is expected to last at least 12 months or result in death. The definition of disability is somewhat subjective, and the decision of disability status is made by a SSA employee. The severity and type of the medical condition, whether the person is currently working, what the person did before the disability, and if the person can do other types of work are all taken into consideration. Further, to be eligible, people are generally required to have worked for a certain amount of time. For example, a 42 year old must have five years of work experience to qualify for benefits.

Individuals who qualify to receive benefits begin to receive them six months after the date the SSA determines that the disability began. Benefits are calculated based on lifetime earnings. After a two year waiting period, SSDI recipients are also eligible for Medicare. Individuals may receive these benefits as long as their medical condition does not improve and they are unable to work. SSDI recipients are allowed to work, as long as their earnings are below the level of substantial gainful activity, which is set at $1,000 per month for 2010.[1]

Supplemental Security Insurance

Like SSDI, the Supplemental Security Insurance (SSI) program is a federal safety net program that provides benefits for disabled people, among other groups. Unlike SSDI, for which individuals qualify based on their medical condition in relationship to work, SSI considers not only one's disability status but also his financial needs as measured by income and assets. Earned income, unearned income, in-kind transfers, and deemed (i.e. spousal) income are all considered, and generally higher income levels mean lower (or no) SSI benefits. There is also a resource limit of $2,000 per individual that includes holdings in cash, a bank account, land, vehicles, and other personal property. The maximum SSI payment for 2010 is $674, and the earnings limit for wages is $1,433. Social Security Insurance recipients are also immediately eligible for Medicaid.

Ticket to Work

Being unable to work is a criteria for receipt of SSDI and (some) SSI benefits, and the Ticket to Work program establishes a mechanism to help disabled workers return to work. Ticket to Work organizes systems of Employer Networks, which consist of employers willing to hire SSDI and SSI recipients, and vocational rehabilitation and other support services. The stated goal is to increase opportunities and choices which help disabled beneficiaries find, enter, and retain employment.

The Americans With Disabilities Act

Passed in 1990 and enacted in 1992, the Americans with Disabilities Act (ADA) was a landmark civil rights policy aimed at protecting individuals with disabilities. The policy grants

[1]The SGA limit for blind SSDI recipients is set higher, at $1,640 per month.

access to and protection against discrimination in the realms of employment, public transportation, public accommodations, and telecommunications. According to this legislation, a person is considered to have a disability if he or she "has a physical or mental impairment that substantially limits one or more major life activities, has a record of such an impairment, or is regarded as having such an impairment."

The employment component of the ADA aims to reduce discrimination in employment, including hiring, firing, promotion, training, terms of employment, and compensation against disabled individuals who are qualified for a given position. An important aspect of the employment section states that employers must provide reasonable accommodation to a disabled employee. This applies to employers with 15 or more employees, as long as it does not provide undue hardship on the firm, which is defined as "an action requiring significant difficulty or expense". Accommodations may take many forms, such as modifying the individual's workspace and equipment, providing flexible work hours, or providing an interpreter.

Any violation of the Americans With Disabilities Act may be brought to the Equal Employment Opportunity Commission (EEOC). The first full year the ADA was in effect, 1993, 15,274 cases were reported to the EEOC. Almost two decades after the passing of the legislation, in 2009, 21,451 cases were brought to the EEOC, resulting in $67.8 million of awards.[2] Unfortunately, this is evidence that discrimination against disabled individuals in the workplace still occurs today.

Individuals With Disabilities Education Act

The Individuals With Disabilities Education Act (IDEA) of 1990 provides equal educational opportunities to disabled children from birth up to age 21.[3] IDEA provides federal funding for states who provide appropriate early intervention, special education, and related services to disabled youth. Not all disabilities are covered, however, as the legislation specifically covers those with sensory limitations, orthopedic impairments, speech impairments, autism, mental

[2] http://www.eeoc.gov/eeoc/statistics/enforcement/ada-charges.cfm

[3] For more, see http://idea.ed.gov.

retardation, traumatic brain injury, and emotional problems.

Under IDEA, disabled youth are provided with individualized education programs to suit their needs and a team of support at school. Transportation, rehabilitation, and psychological services may all be provided as well, if deemed necessary. The major goals of this legislation are for children to receive appropriate special education services and be prepared for further education, employment, and independent living.

2.3 Related Literature

The majority of empirical research on disability has focused on the decision to remain employed or exit the labor force. There is less known about the employment-related outcomes of disabled workers who remain employed. Although a disability may render an individual unable to remain in his current job, that person may adapt to his new set of abilities by changing occupations or employers as opposed to discontinuing employment.

A few studies have explored the role of health on employer or occupational transitions among older workers. Daly and Bound (1996) analyze the characteristics that contribute to employer change for disabled workers using the Health and Retirement Survey (HRS). The authors find that age has a negative impact on the likelihood of employer change and that disabled workers who change employers have a larger decrease in physical job demands compared to those who remain with their current employer. Bound et al. (1999) and Blau and Gilleskie (2001) analyze the dynamic effects of impairment on labor market withdrawal and job change of older workers using the first three waves of the HRS. These papers are some of the only studies in this area to explicitly model disability, controlling for the endogeneity of the variable. Bound et al. (1999) find that a transition from good to poor health has a positive effect on the probability of changing jobs between nine and fourteen percentage points. Blau and Gilleskie (2001) find that transitions from excellent to poor health and from non-disabled to disabled have small negative impacts on the probability of changing jobs. Pelkowski and Berger (2003) extend employment transition analysis to include occupational change, although only consider occupational changes in conjunction with employer change. Their model is dynamic in that they consider the timing of health onset relative to employment spells. The study finds that workers with health problems are 15 percentage points less likely to change employer, but those who do are more likely to also have large occupational changes.

Even fewer researchers have analyzed the role of health on employer and occupational transitions of younger workers. Baldwin and Schumacher (2002) use the SIPP to study voluntary and involuntary employer changes over a 20-month period of disabled persons 16 to 65 years old. Considering a survey responder who has changed employers at any point during this period a "changer", they find that disabled workers are 2.7 percent more likely to have an involuntary job change, but no more or less likely to have a voluntary job change. Differencing the wage between the start and end of the survey, the authors also find that involuntary changes have almost no impact on wages for disabled workers but voluntary changes have a negative impact. Campolieti (2009) uses the Participation and Activity Limitation Survey (PALS) from Canada to study the employer changes of disabled workers across a four-month span. His goal is to identify characteristics that influence the decision to change employers or exit employment relative to remaining with an employer. He finds that, compared to a worker with a mild disability, men with moderate and severe disabilities are respectively 9.1 and 6.9 percentage points more likely to change employers. No comparison is made to non-disabled workers as they are not included in the survey. Campolieti and Krashinsky (2006) analyze the role of employer change on wages of permanently disabled Canadian workers over a one-year period. They find that the disabled workers who return to their pre-injury employer earn over 27 percent more than those who change employers. Each of these three studies treat disability as exogenous and thus may misestimate of the impact of disability if unobservables influence both disability and employment outcomes.

As occupational and employer transitions may be likely forms of adjustment to disability, several papers attempt to learn more information about the role of disability in determining job characteristics. The previously mentioned Daly and Bound (1996) study specifically looks at the role of job characteristics on labor market outcomes for those with a disability. The authors examine whether workers or employers adjust to the onset of a work impairment by changing job characteristics and/or other forms of explicit accommodation. The study identifies the aforementioned trends in their sample of disabled near-retirees and finds that men who change employers reduce the degree of physical job characteristics required, but also were in more physically challenging jobs to begin with. The authors also find that none of the occupational characteristics - physical demand, pace set by others, mental demand, and dealing with people - have a significant effect on the decision to exit the labor force, change employers, or remain with an employer. An early study by Chirikos and Nestel (1981) explores the effect of health on a variety of labor market outcomes of men aged 55 - 69. Constructing an index of limitations to measure health, the authors find that an interaction between impairment and job type is not significant in determining labor force participation. Although the interaction between limitations and jobs are not significant, the analysis does reveal that impaired workers in physical jobs, jobs that involve walking-standing, and jobs that involve sitting-hand/eye coordination, have significantly higher hours worked.

Job characteristics may also, in turn, affect disability status. Cropper (1977) develops a theoretical model of occupational choice as an investment in health. Individuals face a tradeoff between employment at a high paying and high risk job and at a lower paying but safe job. Working in the high risk job increases the probability of illness and also of death. The solution to the model yields that young and old workers will find it optimal to work at the high risk job, but middle aged workers will seek employment in the safe job. The implications of the model are not tested with data, but the paper lays the foundation for considering occupational choice as an investment in health stock. Kemna (1987) develops a basic theoretical model and empirically examines the impact of job characteristics on self reported health. The job characteristics he examines are hazards including if a job is physically strenuous, repetitious, or involves extreme environmental conditions. His findings suggest that being employed in a job with one of these conditions decreases the health of an individual. This effect is magnified for those employed in the occupation for five years or longer, but is smaller if an individual is employed for ten or more years.

Several papers have estimated the direct impact of disability on wages. Using similar approaches, Charles (2003), Mok et al. (2006), Meyer and Mok (2008) find that disability has a persistent negative impact on wages that is worse for chronic and severe disabilities.

After controlling for industry and occupation, Charles (2003) finds that the effect of disability on wages is reduced and notes that “almost half of the recovery men are estimated to make in the two years after onset seems to be the result of changes in industry and occupation.” Examining the wage gap between disabled and non-disabled workers in the years 1972-1984, Baldwin and Johnson (1994) control for experience and tenure, and find that both variables have a positive impact on wages. Contrary to expectations, the disabled workers analyzed have more experience and tenure than non-disabled men, which helps decrease the wage gap between the two groups. In a more recent study, DeLeire (2001) analyzes the wage gap from 1984-1993. In DeLeire’s sample, disabled workers also have higher amounts of employer tenure than the non-disabled, but he does not find that tenure is a significant component of the wage gap.

I contribute to the literature on disability and employment in several ways. First, this research captures more potential employment transitions than previous research which has spanned at most three waves. The data utilized in this study follows individuals for twelve waves with interviews every four months. Second, this is the only study (to my knowledge) to examine the role of disability on both employer and occupational change. That is, I model individuals who change only their occupation, who change only their employer, and who change both occupations and employers.[4] In addition to estimating employment transitions, I also model occupational choice, and in doing so address the fact that occupational characteristics are likely endogenous. Third, I model disability jointly with employment outcomes and wages. I account for both length of disability and severity of disability which is absent from many other related papers. I also measure the degree to which occupational characteristics affect disability status. Finally, the dynamic modeling strategy allows me to measure the the direct impact of disability on wages as well as the indirect effect of disability on wages through employer and occupational tenure.

[4]In any one wave of the SIPP data, 5.3 - 13.8 percent of workers change only occupations, 3.1 - 4.1 percent change only employers, and 0.3 - 0.9 percent change occupations and employers. These percentages also vary by disability status.

Chapter 3

Conceptual Framework

The theoretical model presented in this section motivates the empirical specification that follows. The purpose of the model is to illustrate how disability may affect the likelihood that a worker changes his occupation or employer and, more generally, how disabled workers choose occupations. The model further describes how such employment outcomes affect disability status and wages (through occupational and employer tenure). The focus of this research and the theoretical model is on workers who are employed.

3.1 Employment Transitions

The first goal of the current research is to establish whether or not observed occupational and employer tenure provide an indirect avenue through which disability affects earnings, while controlling for the endogeneity of these transitions. I will begin by outlining a model in which a previously employed individual may continue to work in the same occupation with the same employer, become jobless, change employers and/or change occupations.

The interplay of disability, job mobility, and wages is modeled in a dynamic framework with the following timing assumptions:

1. The individual enters the period knowing his disability status and his disability and employment histories.
2. Four job offers are received each period: an offer from his current job, one from a new occupation, one from a new employer, and one from a new occupation with a new employer.

3. Based on this information, the individual then simultaneously chooses whether or not to work, his occupation, and his employer. Wages of those who work are observed by the researcher.
4. At the end of the period the individual's disability status evolves.

Individuals receive utility in period t from consumption (C_t) and leisure (L_t). The marginal utility of leisure (or disutility of working) varies with disability status (D_t). All else equal, the presence of a disability will likely increase the disutility of working. The amount of disutility caused by a disability depends not only on the nature of the disability, but also on tasks required by the job, and special accommodations made by the employer. Accordingly, the same disability may bring different levels of disutility to identical workers depending on job components (J_t) which include employer and occupational characteristics. Variables that shift preferences also affect utility. These include observable individual characteristics (X_t) and unobservable permanent (μ), time varying (ν_t), and idiosyncratic (ϵ_t) characteristics. Specifically, lifetime utility is represented by:

$$E_t\left[\sum_{t=1}^{T}\beta^t U_t(C_t, L_t; D_t, J_t, X_t, \mu, \nu_t, \epsilon_t)\right]$$

where $E_t[\ ]$ is the expectations operator and β is the discount factor. The individual subscript, i, is dropped for notational ease.

Hours in a period (Ω) are divided between hours of work (H_t) and leisure (L_t):

$$\Omega = H_t + L_t.$$

Total consumption (C_t) is the sum of earned income and unearned income (Y_t).[1] Earned income is the product of hourly wages (W_t) and hours worked. The budget constraint is given by:

$$C_t = W_t * H_t + Y_t.$$

[1]In order to focus on the employment decision, the model abstracts from specific consumption decisions that may depend on disability status, such as medical care consumption or transportation costs.

Substituting the budget and time constraints in to the per period utility function, we have:

$$U_t(W_t * H_t + Y_t, \Omega - H_t; D_t, J_t, X_t, \mu, \nu_t, \epsilon_t).$$

At the beginning of each period an employed individual receives four job offers: a job with his current occupation and employer, a new occupation with his current employer, a new employer in his current occupation, and a new occupation with a new employer. An individual who was not employed in the previous period only has two options: non-employment and employment. These offers specify wages (W_t), and job components (J_t) including hours of work, occupational characteristics, and employer characteristics.

The wage is determined by individual attributes, job components, and market characteristics. An individual's demographic characteristics (X_t) and disability status entering period t (D_t) affect wages. Disability directly affects wages through productivity differences and/or discriminatory practices, although these explanations are indistinguishable (and unexplored) in this model. An individual's firm specific and skill specific expertise may also affect wages. This experience is captured by the individual's employer tenure (ET_t) and occupational tenure (OT_t) up to period t.[2] Job components of the period t alternative (J_t) include hours of work, job characteristics, and employer characteristics. Wages are also affected by local labor market conditions (Z_t). Finally, unobserved permanent (μ) and time-varying characteristics (ν_t) and an idiosyncratic wage shock (ϵ_t^W) influence wages. Wages can be described as:

$$W_t(D_t, OT_t, ET_t, J_t, X_t, Z_t, \mu, \nu_t, \epsilon_t^W). \tag{3.1}$$

where occupational and employer tenure are determined by the history of occupation and employer transitions.

In each period a worker may remain with his current job (which carries with it job components, an hourly wage, and hours of employment), change occupations or employers (which

[2]Note that the measure considered here is tenure, not total work experience.

implies different job components but erases occupational or employer tenure), or become non-employed. The observed employment outcome is a function of individual attributes, disability status, job components, market conditions, and unearned income (Y_t). Large sums of unearned income lead to a low marginal utility of consumption and thus a higher reservation wage. Individuals with high reservation wages are less likely to work, implying that unearned income should have a negative effect on the likelihood of being employed. Employment alternatives are also affected by unobserved characteristics and preferences (μ and ν_t).

Defining all state variables as S_t and allowing disability status to take on a value $d \in [0, D]$, the value function for an individual choosing employment alternative r can be defined as:

$$V_r(S_t, \epsilon_t) = U_t(W_t^r * H_t^r + Y_t, \Omega - H_t^r; d, J_t^r, X_t, \mu, \nu_t) + \epsilon_{rt} + \beta[\sum_{d=0}^{D} P(D_{t+1} = d)V(S_{t+1})].$$

The maximal expected value of lifetime utility is:

$$V(S_t) = E_{t-1}[\max_{q=1,\ldots,R} V_q(S_t, \epsilon_t)] \;\forall\; t.$$

The optimal employment alternative is given by:

$$R_t(D_t, OT_t, ET_t, J_t, X_t, Y_t, Z_t, \mu, \nu_t, \epsilon_t). \tag{3.2}$$

Disability status evolves at the end of the period. Disability depends on observable and unobservable individual characteristics and current disability status.[3] Employment status and job components also affect one's disability status, as job tasks may have a direct effect on health. The length of time a person has been performing job tasks or in a given work environment, as captured by occupational and employer tenure, also influence disability status. Unearned income may also influence one's health, as individuals with high income may be able to purchase more preventative and curative medicine than low income individuals. Specifically,

[3]Section 2.1 provides an in-depth discussion of the sources of endogeneity.

disability in period $t+1$ is described as:

$$D_{t+1}(D_t, OT_{t+1}, ET_{t+1}, J_{t+1}, X_t, Y_t, \mu, \nu_t, \epsilon_t^D). \tag{3.3}$$

Equations (3.1), (3.2), and (3.3) above provide the basis for the empirical model of the first set of analyses that is described in the following section.

3.2 Occupational Characteristics

The second research goal is to understand the interplay between occupational characteristics and disability. In this section, I will elaborate on the above theoretical model to account for occupational choice and the impact of occupational characteristics on disability.

Again, assume that a previously employed individual may become jobless or choose between many different occupations. Per period utility is a function of consumption (C_t), leisure (L_t), disability status (D_t), job components (J_t), observable individual characteristics (X_t) and unobservable permanent (μ), time varying (ν_t), and idiosyncratic (ϵ_t) characteristics:

$$U_t(C_t, L_t; D_t, J_t, X_t, \mu, \nu_t, \epsilon_t).$$

Job components are comprised of employer and occupational characteristics; the focus here is on the later. Occupational characteristics describe the nature of work and specific tasks an employee is required to perform. An individual may select a job based on the required tasks. Specifically, a disabled individual may find that his health limitation makes a particular work requirement uncomfortable to perform, and will choose an occupation that does not involve that task. The tradeoff that a worker faces is that choosing a job with low skill requirements may also come with a lower wage.

In addition to the direct utility received from shifting towards or away from certain occupational tasks, an individual may also benefit from selecting certain occupations if occupational characteristics influence disability status. Recall, from Equation (3.1), that disability is a function of occupational characteristics, among other variables. For example, a person working in a warehouse is likely to do a lot of heavy lifting, which could lead to a back injury. On the other hand, an occupation that has a lot of interpersonal interaction may have indirect health benefits arising from having a support network. Individuals may then choose occupations with the impact of the required tasks on health in mind.

Chapter 4

Empirical Model

4.1 Empirical Specification

In this section, I describe the econometric framework motivated by the theoretical model and used to analyze the data. The estimated equations are linear approximations to optimal decisions that are explained by both observed (endogenous and exogenous) variables and unobserved variables. Note that the employment transition and occupational choice models are estimated separately.

4.1.1 Employment Transitions

The goal of this analysis is to determine the effect of disability on employment, occupational change, employer change, and observed wages. Based on the model of decision making behavior, the employment outcomes of optimizing individuals are observed every period. These employment outcomes (R_t) of those who were employed in the previous period are:

$$r = \begin{cases} 0, & \text{non-employment} \\ 1, & \text{employment with a new employer in a new occupation} \\ 2, & \text{employment with a new employer in the same occupation} \\ 3, & \text{employment with the same employer in a new occupation} \\ 4, & \text{employment with the same employer in the same occupation.} \end{cases}$$

An individual who enters the period non-employed faces alternatives $R_t = r \in \{0, 1\}$ only.

In each period an employed individual chooses whether to remain employed and, if employed, whether to choose the same or a new occupation and employer. The theoretical model implies that job components of each employment alternative influence this decision. However, because observational data generally provide job components of the chosen employment option only, measurement of the impact of employer and occupational characteristics is compromised. Additionally, employer and occupational characteristics are endogenous. Disabled workers may change employers or occupations to accommodate themselves to deteriorations in health. These changes are likely not random as workers may systematically make employment changes as a coping mechanism. Similarly, unobserved individual characteristics may influence both disability and occupational or employer choice. As the focus of this section of the paper is on disentangling the direct impact of disability on wages from the indirect effect captured by occupational and employer tenure and in light of the endogeneity of occupational and employer choice, I do not include contemporaneous or lagged job components such as hours of work, occupational characteristics, or employer characteristics in the employment equation. The following subsection will address the endogeneity of occupational characteristics.

I model the per period employment outcomes indicated by $R_t = r$, which allows for the endogenous determination of occupational and employer tenure. More specifically, conditional on being employed in the previous period ($E_{t-1} = 1$), the probability of a particular employment outcome in period t relative to non-employment (expressed in log odds) is given by:

$$ln\left[\frac{Pr(R_t = r|E_{t-1} = 1)}{Pr(R_t = 0|E_{t-1} = 1)}\right] = \alpha_{r0} + \alpha_{r1}S_t^D + \alpha_{r2}S_t^E + \alpha_{r3}X_t + \alpha_{r4}Y_t + \alpha_{r5}Z_t + \mu_1^r + \upsilon_{1t}^r, \text{ r=1,..,4.} \tag{4.1}$$

The vector of variables describing one's disability history entering period t, S_t^D, includes disability status, disability severity status, the number of periods since first disability onset if the individual entered the sample disabled, and disability tenure if the individual entered the sample without a disability. Employment history entering the period, S_t^E, is described by the number of consecutive periods an individual has worked for the same employer (employer tenure), the number of consecutive periods an individual has worked in the same occupation (occupational tenure), and the number of periods of recent non-employment (which will be zero for those employed in period $t-1$). The observed exogenous variables (X_t) include age, race, marital status, number of children, educational attainment, urbanicity, and region. Unearned income is measured as the amount of non-transfer income and is denoted Y_t. Market characteristics are contained in Z_t, which includes the average local unemployment rate.[1] Note that unobserved permanent and time-varying individual components affect all estimated equations.[2]

A person who was nonemployed in period $t-1$ has only two alternatives: to become employed or remain jobless. Expressed in log odds, the probability of entering employment is:

$$ln\left[\frac{Pr(E_t = 1|E_{t-1} = 0)}{Pr(E_t = 0|E_{t-1} = 0)}\right] = \beta_0 + \beta_1 S_t^D + \beta_2 S_t^E + \beta_3 X_t + \beta_4 Y_t + \beta_5 Z_t + \mu_2 + \upsilon_{2t}. \quad (4.2)$$

Here, the relevant variable from the employment history vector (S_t^E) is the length of time a person has been jobless, as the occupational and employer tenure variables are zero.

The natural log of observed wages in period t, conditional on employment in period t is:

$$lnW_t = \delta_0 + \delta_1 S_t^D + \delta_2 S_{t+1}^E + \delta_3 X_t + \delta_4 Z_t + \mu_3 + \upsilon_{3t} + \epsilon_{3t}. \quad (4.3)$$

The updated employment history (S_{t+1}^E) accounts for current employment choices and includes hours worked, employer size, dummy variables for occupational category, employer and occupational tenure.[3] Note that observed wages are also explained by disability entering period t and an interaction between disability status and each tenure variable.

Disability status evolves at the end of the period. Disability status is defined as three

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[1]The average local unemployment rate is defined as the unemployment rate in a given area defined by the SIPP, which is roughly a metropolitan statistical area.

[2]The joint distribution of the μs and the joint distribution of the υ_ts will be discussed in Section 4.2.

[3]I acknowledge that hours worked, employer size, and occupation are likely endogenous. However, I take the stance that the omitted variable bias caused by ignoring these variables may be worse than estimation including these endogenous variables. As the effect of these variables is not the focus in this section of the paper, I include them in estimation yet do not discuss their marginal effects. A more careful analyses of occupational choice is conducted later in the dissertation.

different levels: non-disabled, moderately disabled, and severely disabled (d = 0, 1, 2). Exogenous individual characteristics, current disability status, the characteristics implied by current period occupational and employment choices, unearned income, and unobserved individual characteristics influence period $t+1$ disability.[4] More specifically, in log odds, the probability of a disability is given by:

$$ln\left[\frac{Pr(D_{t+1}=d)}{Pr(D_{t+1}=0)}\right] = \gamma_{d0} + \gamma_{d1}S_t^D + \gamma_{d2}S_{t+1}^E + \gamma_{d3}X_t + \gamma_{d4}Y_t + \mu_4^d + \upsilon_{4t}^d, d = 1, 2. \qquad (4.4)$$

4.1.2 Occupational Characteristics

In this section, I focus on the empirical specifications used to determine how individuals choose occupations. This model is similar to the model for employer transitions, except instead of choosing which of the $R = 5$ transitions to make, here individuals choose among R occupations:

$$r = \begin{cases} 0, \text{ non-employment} \\ 1, \text{ employment in occupation 1} \\ 2, \text{ employment in occupation 2} \\ ... \\ R, \text{ employment in occupation R.} \end{cases}$$

The theoretical model implies that the optimal outcome is the one that maximizes current and future utility. The individual, then, is choosing between occupations, and the outcome depends on both individual and occupational characteristics. To incorporate both sets of variables, the probability of an unobserved occupational outcome is estimated as a mixed

[4]Refer to Footnote 3 above.

conditional logit model.[5] Empirically, occupational choice is estimated as:

$$ln\left[\frac{Pr(R_t = r)}{Pr(R_t = 0)}\right] = \alpha_{r0} + \alpha_{r1}S_t^D + \alpha_{r2}S_t^E + \alpha_3 O_{rt} + \alpha_{r4}X_t + \alpha_{r5}Y_t + \alpha_{r6}Z_t + \mu_1^r + \upsilon_{1t}^r, \text{ r=1,..,R.} \tag{4.5}$$

In the above equation, the individual subscripts have been relaxed, for notational ease. Occupational outcome is a function of several individual characteristics including disability history, S_t^D, employment history, S_t^E, observed exogenous variables, X_t, unearned income, Y_t, and market characteristics, Z_t. Occupational choice also depends on occupational characteristics, O_{rt}, which are occupation specific.

In estimating such a model, I have made the assumption that all occupations are available to all individuals. This, of course, is unlikely to be completely accurate, as many occupations have educational and training requirements that are not currently held by much of the population. In future research, a mechanism in which the outcomes are weighted by the probability that an outcome is available to each individual could strengthen the estimation method. Still, this approach is an improvement over methods that assume that occupations are exogenous.

4.2 Estimation Technique

Discrete Factor Random Effects

Estimation of the empirical equations is performed using a nonlinear random effects estimation technique, referred to as the Discrete Factor Random Effects method (DFRE). This approach controls for variables that are unobservable to the researcher and may impact all equations, as failure to control for these unobservables may result in biased estimates. The DFRE method estimates the distribution of these unobserved variables by decomposing the error term into three parts: permanent heterogeneity (μ_n^o), time-varying heterogeneity (υ_{nt}^o), and random error term (ϵ_{nt}^o). This decomposition is applied to all n estimated equations as

[5]Recall that multinomial logit models require that control variables be the same for all options. Thus, individual characteristics are valid control variables. However, as occupations have characteristics that vary across alternatives, these characteristics are not valid covariates for a mutinomial logit model. For more see Appendix C.1.

well as for each outcome o of multinomial logit equations. The random component of the error is iid for continuous equations, and extreme value distributed for logit equations. Allowing the unobserved heterogeneity to be non-linear, the error term for all equations may be written as:

$$\xi_{nt}^{o} = \mu_{n}^{o} + \upsilon_{nt}^{o} + \epsilon_{nt}^{o} \tag{4.6}$$

where μ and υ_t are assumed to be correlated across equations while ϵ_t is random and uncorrelated.[6]

The cumulative distribution function of each unobserved heterogeneity component is approximated by a discrete stepwise function. The function is estimated with points of support for the distribution of unobserved factors.[7] This flexible estimation technique does not impose joint normality on the error terms as is standard in many maximum likelihood techniques (Heckman and Singer (1984)). Using a Monte Carlo simulation, Mroz (1999) shows that when the true distribution of the error terms is jointly normal the Discrete Factor Random Effects method performs as well as maximum likelihood estimation. However, when the distribution is not normal, the DFRE method performs better in terms of precision and bias.

This approach offers many benefits over the fixed-effects method, which is commonly used with panel data to control for permanent individual unobservables over time. While fixed effects account for permanent individual heterogeneity only, I specify discrete approximations to both permanent and time-varying unobserved individual heterogeneity using the DFRE method. Additionally, the use of fixed effects to capture permanent unobservables would not allow for measurement of the effect of observable non-time varying variables on wages. Lastly, while both methods introduce additional estimated parameters, the discrete distributions of the random effects add only a fraction of the additional parameters required by the fixed effects method.

[6] Time-varying heterogeneity is not serially correlated. However, to the extent that a time-varying shock effects a contemporaneous variable and that variable effects future values, the effect of the shock will be fully absorbed in observable characteristics.

[7] For more details, see Appendix C.2.

Initial Conditions and Attrition

Accompanying the many benefits of longitudinal data on individuals is the restriction that behavior is observed for a subset of the individuals' decision making periods. More specifically, individuals enter the research sample with non-zero values of the endogenous employment and disability history variables. Accordingly, the equations outlined above that utilize lagged information cannot be estimated for the first period of the survey. These "pre-sample" decisions are likely correlated with unobserved permanent individual characteristics that also influence observed ("within sample") outcomes. To account for this correlation, I model the initial state variables as reduced form equations using only contemporaneous variables that also depend on permanent unobserved heterogeneity. I estimate equations for initial employer tenure, occupational tenure, and disability status jointly with the per-period equations for employment outcomes, wages, and disability status.

Observations on individuals in the research sample are also right censored; individuals attrit from the sample each period. In order to account for the potential of non-random attrition, I estimate the probability of attriting as a function of observed behavior as well as permanent and time-varying unobservables. This attrition equation is jointly estimated with the other equations in the model.

Identification

In a dynamic model with many outcomes, we have to be concerned about properly identifying effects of interest. In particular, we need to measure the causal effect of occupation and employer tenure on wages and the casual effect of employment outcomes on disability. Identification requires that a variable explain observed employment outcomes that has no independent effect on wages or on disability conditional on the outcome. The theoretical model implies that unearned income affects choice of employment alternative but does not impact wages. Similarly, average unemployment rates, which affect employment alternatives, are excluded from the disability equation. Both variables are significant in the equations modeled, and a likelihood ratio test of joint significance produces a p-value of 0.001. Further, the variables are jointly insignificant in the equations from which they are excluded, supporting the validity of the instruments.

The effect of disability on employment outcomes must also be properly identified. Disability status entering period t is shifted by previous per period variables, some exogenous and some endogenous. The endogenous variables (such as employment outcomes in the previous period) are functions of exogenous variables (such as average unemployment rates). Therefore, the entire history of exogenous variables provides exogenous variation and identifies the causal effect of disability on employment outcomes (Arellano and Bond, 1991).

Initial disability status is identified by indicators for whether one served in the Vietnam War and whether one served in any other major military conflict. These variables influence initial disability status, but do not affect subsequent disability probabilities conditional on disability entering the period. Initial occupational tenure and initial employer tenure are both identified by the unemployment rate at the time an individual graduated from his highest level of education. These variables do not affect subsequent employment outcomes but are significant in the initial occupational tenure and employer tenure equations.

4.3 Likelihood Function

For the model of employment transitions and wages, an individual's contribution to the likelihood function, unconditional on the unobserved heterogeneity, is:

$$\begin{aligned} L_i(\theta,\rho,\psi) = \quad & \sum_{k=1}^{K} \rho_k \Bigg\{ \prod_{e=0}^{6} \mathrm{P}(ET_1 = e|\mu_{6k}^{e}) 1[ET_{i1} = e] \prod_{o=0}^{6} \mathrm{P}(OT_1 = o|\mu_{7k}^{o}) 1[OT_{i1} = o] \\ & \prod_{d=0}^{2} \mathrm{P}(D_{t+1} = d|\mu_{5k}^{d}, \upsilon_{5t\ell}^{d}) 1[D_{it+1} = d] \\ & \prod_{t=1}^{T} \sum_{\ell=1}^{L} \psi_\ell \Bigg[\prod_{r=0}^{R} \mathrm{P}(R_t = r|\mu_{1k}^{r}, \upsilon_{1t\ell}^{r}) 1[R_{it} = r] 1[E_{it-1} = 1] \\ & \mathrm{P}(E_t = 1|\mu_{2k}, \upsilon_{2t\ell})^{E_{it}} [1 - \mathrm{P}(E_t = 1|\mu_{2k}, \upsilon_{2t\ell})]^{1-E_{it}} 1[E_{it-1} = 0] \\ & [\frac{1}{\sigma} \Phi(\ln W_t|\mu_{3k}, \upsilon_{3t\ell})]^{E_{it}} \\ & \prod_{d=0}^{2} \mathrm{P}(D_{t+1} = d|\mu_{4k}^{d}, \upsilon_{4t\ell}^{d}) 1[D_{it+1} = d] \Bigg] \Bigg\} \end{aligned}$$

where θ denotes the parameters that are estimated in the model. ρ_k is the estimated joint probability of the k^{th} permanent mass point, which is given by:

$$\rho_k = \mathrm{P}(\mu_1^0 = \mu_{1k}^0, ..., \mu_1^4 = \mu_{1k}^4, \mu_2 = \mu_{2k}, \mu_3 = \mu_{3k}, \mu_4^0 = \mu_{4k}^0, .., \mu_4^2 = \mu_{4k}^2,$$
$$\mu_5^0 = \mu_{5k}^0, ..., \mu_5^2 = \mu_{5k}^2, \mu_6^0 = \mu_{6k}^0, ..., \mu_6^6 = \mu_{6k}^6, \mu_7^0 = \mu_{7k}^0, ..., \mu_7^6 = \mu_{7k}^6).$$

ψ_ℓ is the estimated joint probability of the ℓ^{th} time-varying mass point and is given by:

$$\psi_\ell = \mathrm{P}(\upsilon_1^0 = \upsilon_{1\ell}^0, ..., \upsilon_1^4 = \upsilon_{1\ell}^4, \upsilon_2 = \upsilon_{2\ell}, \upsilon_3 = \upsilon_{3\ell}, \upsilon_4^0 = \upsilon_{4\ell}^0, ..., \upsilon_4^2 = \upsilon_{4\ell}^2).$$

Time-varying heterogeneity is excluded from the initial period equations.

The likelihood function described is the basis for the maximum likelihood random effects estimation technique used to analyze the data. The data used in the analysis is described in the following section.

Chapter 5

Data

5.1 Individual-Level Data

The data used to estimate the model come from the 1996 panel of the Survey of Income and Program Participation (SIPP). Although the SIPP has been conducted as recently as 2004, I have chosen to use the 1996 panel because it runs for four years, and is the longest running of all panels. The 1996 panel also has the most sample members of all SIPP panels.

The SIPP provides detailed longitudinal information on income amounts and sources as well as the participation in and eligibility for federal, state, and local government programs. Although the SIPP does not directly focus on disability or employment, much information on these topics is provided. The SIPP interviews participants every four months instead of every year as is standard in many surveys.[1] This structure makes the SIPP particularly appealing to study disability and employment, as these outcomes may fluctuate several times within a year and may be subject to recall bias if survey intervals are long.[2]

The focus of my analysis is on the employment behavior of males during their prime working years as it relates to disability. Accordingly, the research sample includes men over the age of

[1] At every interview, respondents are asked to report current information as well as recall certain information from each of the past three months. For example, a person interviewed in April, would also be asked about information in January, February, March, and April. Unfortunately, respondents are only asked to recall disability status, employer, and occupation for the current month. Accordingly, I am unable to exploit all information available in the SIPP and only analyze the data from every fourth month.

[2] Blau (1994) finds that yearly data sets underestimate employment transitions among near-retirement aged men compared to quarterly data.

Table 5.1: Sample Determination

Criterion	Individuals
Male Survey Respondent	56,003
Aged 25 to 60	26,253
Six Consecutive Periods	14,963

25 (inclusive) and less than 60 (exclusive). I retain individuals with information on disability, employment, occupation, and hours worked for at least six consecutive periods (two years). Of the 56,003 men surveyed, 26,253 were between the ages of 25 and 60. Of those, 11,290 did not have six or more consecutive periods of information and were dropped. The research sample consists of 14,963 individuals and 155,045 person-wave observations. The details of the sample determination are contained in Table 5.1.

It should be the case that those excluded due to missing variables are similar to the research sample, and the two groups are compared in Table 5.2. For my research sample, the averages are calculated based on the periods that the individual would be used in analysis, i.e. a consecutive sequence. Thus each individual could contribute anywhere between six and twelve periods worth of information, and the number of periods of information contributed can also vary by variable. The averages for the individuals that are dropped from my sample due to missing values are calculated based on all periods of available information. The two samples are similar across many dimensions, with the exception of marital status. The 13 percentage point difference in the incidence of marriage between the two groups is likely attributed to sample design. The SIPP surveys by households, so if a person is unmarried he is more likely to have entered the household after they survey has begun or to leave the household and thus not be included in the sample. However, the research sample is not statistically different from the excluded sample in terms of two of the variables of focus: disability status and employment.

One of the main goals of the analysis is to measure the dynamic impact of disability on employment outcomes. Figure 5.1 illustrates how employment rates change over time as disability evolves. The horizontal axis, disability tenure, represents the number of periods before or after the onset of a disability (denoted as a disability tenure of 0) for disability spells that begin in the survey. If a person is disabled, recovers, and becomes disabled again

Table 5.2: Comparison of The Research Sample to Persons Dropped Due to Missing Variables

Variable	Research Sample	Dropped Sample	Difference
Age	41.3	39.9	1.39
	(9.3)	(9.9)	
Non-White	0.15	0.17	-0.02
	(0.36)	(0.37)	
Education	13.2	13.0	0.24
	(3.0)	(2.8)	
Married	0.69	0.55	0.13
	(0.45)	(0.49)	
Non-Metropolitan	0.20	0.18	-0.02
	(0.39)	(0.37)	
Disabled	0.11	0.11	-0.00
	(0.27)	(0.28)	
Employed	0.88	0.87	-0.01
	(0.28)	(0.30)	
N	14,964	11,289	

(Standard Deviations in Parentheses)

he is considered to be in a new spell of disability and his tenure would restart at zero upon the beginning of the second disability spell. The graph shows that the employment rate is relatively stable prior to the onset of disability and plunges and remains low once disability occurs.[3]

Individuals with disabilities differ not only by length of time disabled but also by the severity of their disability. Separating the disabled into two groups, Figure 5.2 shows changes in employment by length of disability for the moderately disabled and the severely disabled. The progression of employment rates differs vastly across these two groups and it appears that it is the severely disabled who are driving the drop in employment rates among the disabled.

The non-disabled, the moderately disabled, and the severely disabled differ by exogenous characteristics. Table 5.3 displays summary statistics separately for each group. Of the 14,963 individuals in the research sample, 3,068 (20 percent) are disabled at some point during the four year period, with variation in the length of disability. These 3,068 individuals contribute 16,479

[3]Note that the sample composition is considerably smaller (and potentially different) the longer the number of quarters before or after onset. That is, the employment rates in the left and right tails of the figure are weighted towards more and less healthy individuals, respectively.

Figure 5.1: Employment Rate by Disability Tenure

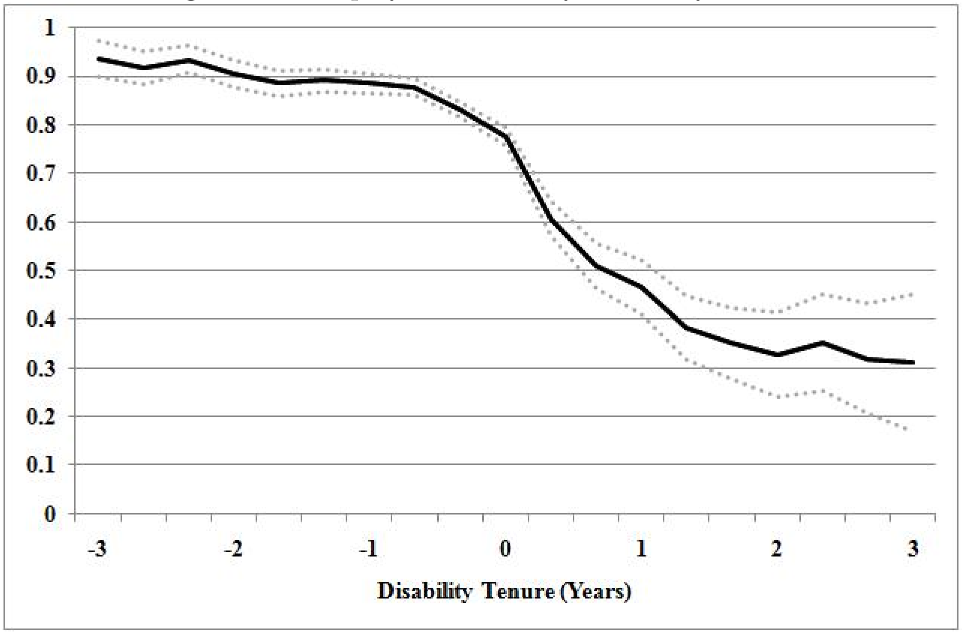
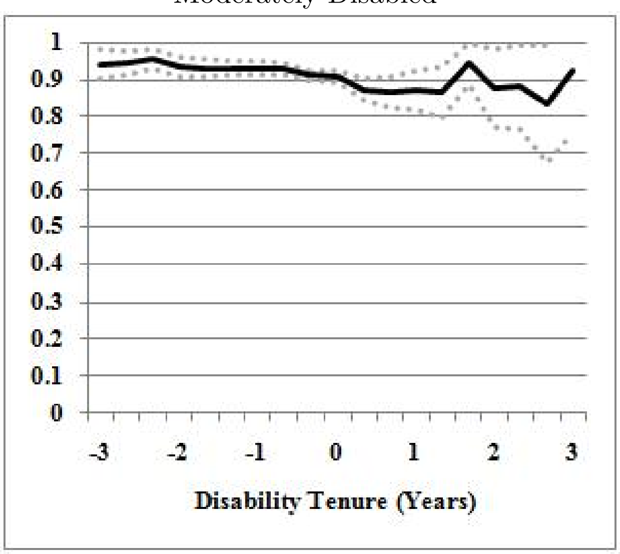


Figure 5.2: Employment Rate by Disability Tenure and Severity

Moderately Disabled



Severely Disabled

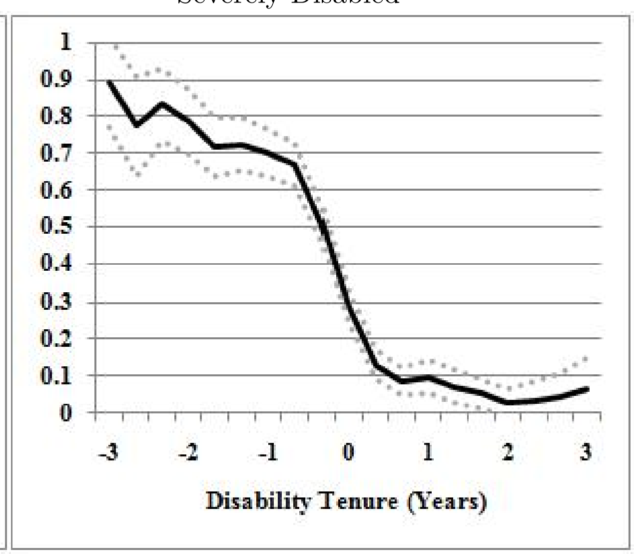


Table 5.3: Comparison of the Non-Disabled to the Disabled

Variable	Non-Disabled		Moderately Disabled		Severely Disabled	
Age (in years)	40.99	(9.07)	43.70	(9.07)	46.24	(8.87)
Non-White	0.14	(0.34)	0.14	(0.34)	0.26	(0.44)
Years of Education	13.46	(2.87)	12.40	(2.97)	10.62	(3.55)
Married	0.72	(0.45)	0.59	(0.49)	0.45	(0.50)
Non-Metropolitan Residence	0.20	(0.40)	0.25	(0.43)	0.28	(0.45)
Employed	0.95	(0.22)	0.89	(0.31)	0.04	(0.19)
Observations (person-wave)	138,566		6,208		10,271	

Note: Standard Deviations in Parentheses.

Table 5.4: Comparison of the Employed Non-Disabled to the Employed Disabled

Variable	Non-Disabled		Moderately Disabled		Severely Disabled	
Employed$_{t-1}$						
No Change (%)	87.83	(32.69)	79.06	(40.73)	29.66	(45.74)
Become Jobless (%)	1.41	(11.78)	4.97	(21.74)	58.10	(49.41)
Switch Occupation (%)	6.74	(25.08)	8.38	(27.71)	8.56	(28.02)
Switch Employer (%)	3.51	(18.39)	6.62	(24.86)	2.45	(15.47)
Switch Occupation and Employer (%)	0.51	(7.11)	1.03	(10.10)	1.22	(11.01)
Observations (person-wave)	119,026		5,049		327	
Non-Employed$_{t-1}$						
Remain Jobless (%)	74.29	(43.70)	76.74	(42.28)	96.72	(17.82)
Become Employed (%)	25.71	(43.70)	23.26	(42.28)	3.28	(17.82)
Observations (person-wave)	6,232		589		8,859	
Wage (1996 $)	10.74	(13.39)	7.42	(15.51)	5.75	(8.74)
Observations (person-wave)	118,952		4,935		428	

Note: Standard Deviations in Parentheses.

periods of disability to the person-wave observations. The disabled are older, less educated, less likely to be married and live outside of metropolitan areas. While the moderately disabled are slightly less likely to be employed than the non-disabled, very few of the severely disabled work.

Table 5.4 reveals that labor market transitions vary across disability status. Non-disabled and moderately disabled individuals who were employed in the previous period are unlikely to become jobless in the current period, but over half of severely disabled workers become jobless. Over 8.3 percent of workers with any level of disability change occupations compared to 6.7 percent of non-disabled workers. Moderately disabled workers as a group are the most likely to change employers. Conversely, severely disabled workers are the group least likely to change employers. Moderate and severely disabled workers are also twice as likely to change occupations and employers as are non-disabled workers. Non-disabled and moderately disabled individuals who were not employed in the previous period are over seven times more likely to gain employment than severely disabled workers. Of individuals who are employed, wages decrease with disability severity. Non-disabled workers have an average wage of \$10.74 an hour, non-severely disabled workers earn \$7.42 an hour, and the severely disabled make just \$5.75 an hour.[4] This research examines the extent to which reductions in tenure associated with job transitions contribute to this wage gap.

Disability is a heterogeneous concept, and there are likely many differences among disabled individuals beyond chronicity and severity. One key difference between survey respondents with a disability is the nature of the disability, as the SIPP specifically asks if the individual has a physical or mental condition. Unfortunately, the source of disability is not asked in every interview wave. Of the twelve interviews, this follow up question is only asked in waves two, five, and eleven. The disability sources are listed in Table 5.5, and I have assigned each condition as either a physical or mental limitation. Due to the large number of individuals for whom this information is missing, I am unable to utilize this information in my estimation. However, to understand the sample population, I have presented a description of the disability

[4] The minimum wages for the years 1996-2000 (in 1996 dollars) are: \$4.75, \$5.03, \$4.96, \$4.85, \$4.69.

source in Table 5.6. All estimates in the table are a pooled cross section across each of these three waves of individuals who attribute their disability source.[5]

Table 5.6 confirms that there are distinct differences between those with physical and those with mental disabilities. Although individuals with a mental disability are younger, on average the group is less likely to be married, white, or live in a metropolitan area, and has a lower education level. Individuals with a mental disability are also more likely to be severely disabled with a chronic disability compared to those with a physical disability. The groups also differ by employment status, as those with a mental disability are less likely to be employed and work lower hours when they are employed. Physically and mentally disabled individuals differ across a number of observed variables, and these observed differences will be accounted for in estimation.

[5] In each cross section, approximately 10 percent of disabled individuals report their disability as "other".

Table 5.5: Definition of Disability Source

Physical	Mental
AIDS	Alcohol Problem
Arthritis	Drug Problem
Back Problem	Learning Disability
Blindness	Mental/Emotional Problem
Broken Bone	Mental Retardation
Cancer	Senility/Dementia
Cerebral Palsy	Alzheimer's
Deafness	Speech Disorder
Epilepsy	
Head/Spine Injury	
Heart Trouble	
Hernia	
High Blood Pressure	
Kidney Stones	
Lung/Respiratory Trouble	
Missing Limb	
Paralysis	
Stiffness/Deformity of Limb	
Stomach Trouble	
Stroke	
Thyroid Trouble	
Tumor/Cyst	

Table 5.6: Physical vs Mental

Variable	Physical	Mental
Age	45.3	41.3
Non-White (%)	24.0	17.0
Married (%)	61.8	29.6
Education (Years)	13.1	11.5
Non-Metropolitan (%)	26.0	28.6
Severely Disabled	41.3	71.0
Total Time Disabled (Years)	13.9	21.5
Employed (%)	66.2	26.1
Hours Worked if Employed	41.6	31.2
Person-Observations	7,495	1,417
Percent	84.1%	15.9%

Table 5.7: Definition of Dependent and Key Explanatory Variables

Variable	Description
Dependent Variables	
Disabled	Indicator equal to 1 if the respondent reports having a work limitation
Severely Disabled	Indicator equal to 1 if the respondent reports having a work limitation that is severe enough to prevent work
Employed	Indicator equal to 1 if employed
Wage	Hourly wage calculated as weekly earnings divided by weekly hours worked
Employment Transition	
No Transition	Remains with the same occupation and same employer
Become Jobless	Not employed
Change Occupation	Work with a new occupation and the same employer
Change Employers	Work with the same occupation and a new employer
Change Both	Work with a new occupation and a new employer
Occupational Choice	50 choice variable representing the 50 observed occupations
Key Explanatory Variables	
Time Disabled	Length of time (in years) the individual has been in a spell of disability that began in the survey
Total Time Disabled	Length of time (in years) since the individual reported his first spell of disability
Occupational Tenure	Length of time the individual has been continuously employed in his current occupation
Employer Tenure	Length of time the individual has been continuously employed with his current employer

5.2 Occupational Data

In addition to the SIPP data, I also use the Dictionary of Occupational Titles (DOT). The DOT is a comprehensive listing of thousands of jobs and the skills and tasks required in each job. It was originally intended to be a guide to occupational placement, but has been used in several economic studies as data sets (see Gronberg and Reed (1994), Smith et al. (1997), Autor et. al (2003), or Wolff (2003)). I use the occupational code and definition trailer of each occupation, which assign scores to eight job characteristics.

The last update to the DOT was made in 1991. Although I am using the SIPP between 1996 and 2000, the 1991 version of the DOT is sufficient in that there are no newly created occupations in the SIPP that are not defined by the DOT. Since 1999, the DOT has been succeeded by the Occupation Information Network (O*Net). O*Net is much more detailed than the DOT which is helpful for career placement (but is nearly impossible to be viewed as a concise data set). O*Net does not have a uniform listing of characteristics on which it ranks all occupations. Instead each occupation is ranked on ten main categories, each of which have subcategories listing the importance of narrowly defined tasks. Some of the categories have over 50 sub-categories indicating the importance of each subcategory to the job. The subcategories can vary across occupation: for example, a professional athlete and a chemist may have very few of the same subcategories. Thus, O*Net has hundreds of tasks, which would be prohibitively difficult to analyze and interpret in an economic study.

The occupation codes used in the SIPP are the 1990 Census codes. There are just over 500 census codes, and using a crosswalk provided by the National Crosswalk Center this translates to over 12,000 DOT codes. Accordingly, each SIPP occupation may have multiple DOT occupations codes. To assign one set of characteristics to each SIPP occupation code, the median of the characteristics for each DOT code was used. If the median occurred between two numbers, I assigned the more difficult value to the SIPP code.

The eight job characteristics I analyze are the degree to which a worker in a given occupation works with data, people, and things (inanimate objects), the amount of general educational development needed in reasoning, mathematics, and language, the amount of specific vocational preparation (SVP) required, as well as the strength requirement.[6] For example, the data category ranges from the least intensive score of one (which involves, in this case, comparing data) up to seven (which involves synthesizing data). The range of all occupational characteristics can be seen in Table 5.8. Examples of occupations by characteristics levels are contained in Table 5.9.

Table 5.8: Definition of Job Characteristics

Variable	Minimum		Maximum	
Data	1	Comparing	7	Synthesizing
People	1	Helping	9	Mentoring
Things	1	Handling	8	Setting Up
Reasoning	1	Commonsense	6	Conceptual
Math	1	Arithmetic	6	Advanced Calculus/Statistics
Language	1	Word Recognition, Sentences	6	Read/Write Literature, Critique
SVP	1	Short Demonstration	8	4-10 years
Strength	1	Sedentary	5	Heavy Work

Workers are found to choose jobs differently by disability status. The distribution of characteristics by disability status can be found in Figure 5.3. The figure reveals that disabled workers have lower levels of work with data, people, reasoning, math, language, and training time than non-disabled workers. However, disabled workers do not appear to be significantly different from non-disabled workers in regards to working with things, and have higher strength

[6]DOT rankings have been shifted so that 0 represents a low requirement level, and higher values indicate increased requirements in that category.

Table 5.9: Examples of Occupations

Variable	Minimum		Maximum	
Data	1	Farm Worker	7	Lobbyist
People	1	Dough Mixer	9	Police Chief
Things	1	Weigher	8	Model Maker
Reasoning	1	Fruit Cutter	6	Chemist
Math	1	Lifeguard	6	Programmer
Language	1	Cleaner	6	Editor
SVP	1	Laborer	8	Surgeon
Strength	1	Statistician	5	Fire Fighter

Table 5.10: Characteristics by Disability Status

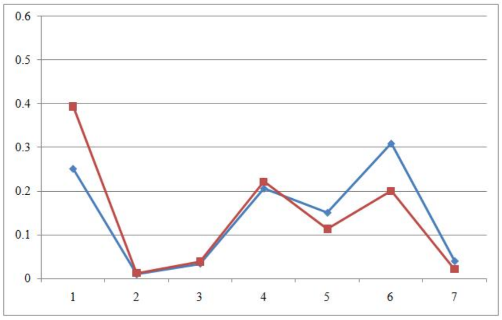
Variable	Non-Disabled	Moderately Disabled	Severely Disabled
Data	4.1	3.4	2.9
People	2.8	2.3	1.9
Things	3.4	3.2	3.3
Reasoning	3.8	3.4	3.2
Math	2.8	2.4	2.1
Language	3.2	2.7	2.4
SVP	2.6	1.7	1.4
Strength	2.2	2.4	2.5

requirements. Or instead of graphs, Table 5.10 compares the averages of occupational characteristics by disability status. This table supports the graphs in the notion that disabled workers are employed in occupations with lower levels of all occupational characteristics, with the exception of strength.

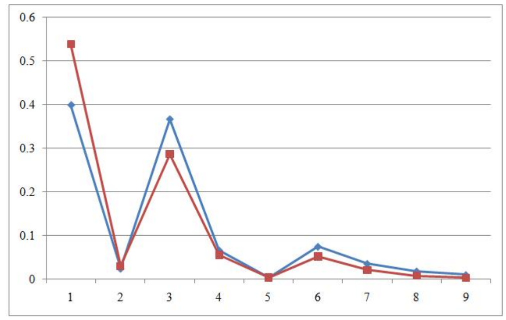
In addition to estimating occupational choice, this research will analyze the effects that these occupational characteristics have on disability status. For example, perhaps the choice of disabled individuals to continue in occupations with high strength requirements contribute to continued disability.

For my analysis involving occupational choice, I discretize the job characteristics to represent a low or high level of that characteristic. The cut-off values were assigned so that occupations with the lowest 50 percent of job characteristics had values assigned to 0, and the other half were assigned to 1. The discrete assignments can be seen in Table 5.11. The discrete job characteristics were then used to define occupations. For example, an economist has occupational characteristics of: data 7, people 3, things 2, reasoning 5, math 5, language 5, svp 8, strength 1. These characteristics would be assigned to discrete values of data 1, people, 1, things, 0, reasoning 1, math 1, language 1, svp 1, strength 0. Other occupations are also assigned these values including mathematicians, statisticians, and sociologists. Condensing occupations in this manner results in 50 unique occupations, defined by their occupational characteristics. These occupations represent the 50 alternatives individuals have when choosing occupations in the model.

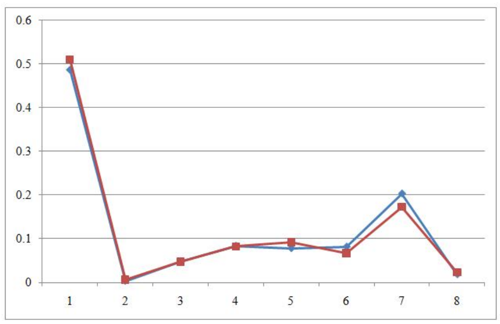
Figure 5.3: Distribution of Job Characteristics by Disability Status



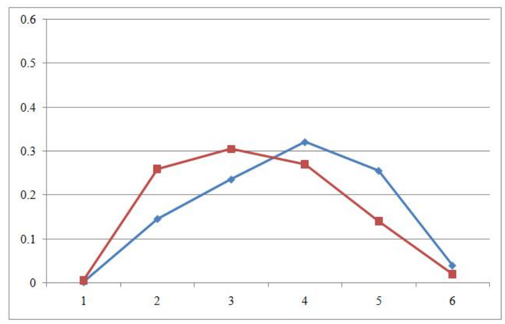
(a) Data



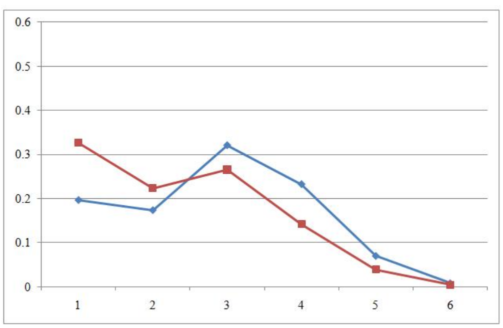
(b) People



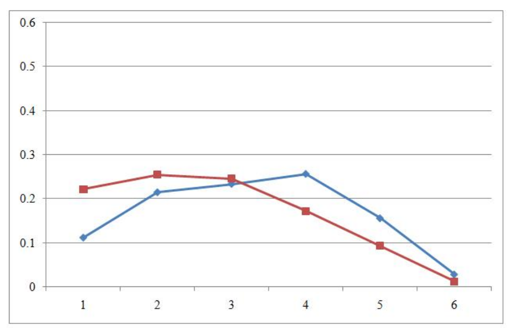
(c) Things



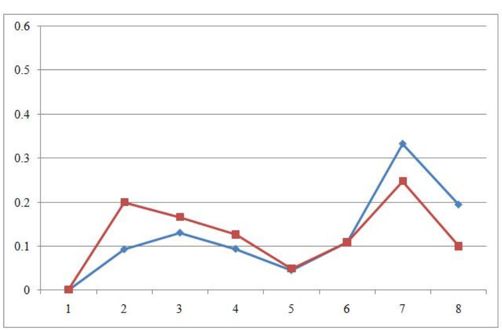
(d) Reasoning



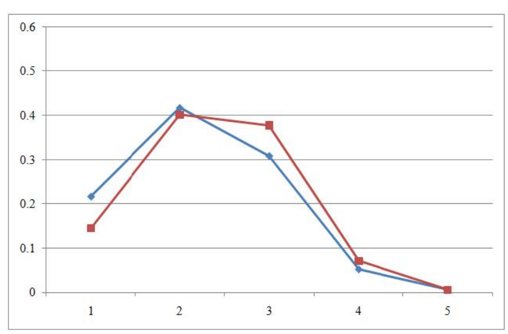
(e) Math



(f) Language



(g) Specific Vocational Preparation



(h) Strength

Table 5.11: Discretizing Job Characteristics

Variable	Cut-Off
Data	4
People	2
Things	3
Reasoning	3
Math	2
Language	3
SVP	6
Strength	2

Chapter 6

Results

In this chapter, I will present the results of the empirical estimation for both models. First, I will discuss the results from the model of employment transitions. Then, I will follow with the results from the model of occupational choice. Finally, I will compare estimates of the wage equation from both models.

6.1 Employment Transitions

I jointly estimate equations for the employment outcome for the employed, employment for the jobless, log wages, disability status, and equations for initial tenure, initial disability status, and attrition. The equations are estimated simultaneously, allowing for unobserved permanent and time-varying heterogeneity. Coefficient estimates are available in Appendix Tables B.1, B.2, B.3, and B.4.

The accuracy of a model can be determined by comparing the actual values with the predicted values determined by the model. The first column of Table 6.1 contains the actual sample proportions of each dependent variable. The second column contains predicted values from my model obtained by multiplying observed explanatory variables by the predicted coefficient values and integrating over the unobserved heterogeneity. These predictions, mapped to a [0,1] line, and a random uniform draw determine the simulated values of endogenous right hand side variables which are updated sequentially. The predictions are similar to the actual sample proportions, suggesting the model fits the data well. Additional evidence that the dynamic model fits the observed outcomes over time is shown graphically in Table A.1.

Table 6.1: Predicted Values: Employment Transitions

Variable	Actual	Predicted
Employment Rate	0.887	0.889
No Change in Employment	0.873	0.867
Become Jobless	0.017	0.019
Change Occupation	0.068	0.072
Change Employer	0.036	0.037
Change Both	0.005	0.006
Moderately Disabled	0.039	0.038
Severely Disabled	0.067	0.061
Ln(Wage) ($E_t = 1$)	2.17	2.15

Marginal Effects

In Table 6.2, I present the marginal effects of disability on employment outcomes from two specifications. The marginal effects presented are one period effects averaged over all individuals in the sample. Standard errors are parametrically bootstrapped by repeatedly perturbing estimated coefficients from the variance-covariance matrix 100 times. Model 1 treats the endogenous variables (S_t^E, S_t^D) as exogenous by not controlling for the unobserved heterogeneity. It produces biased effects of these variables. Model 2, the preferred model, uses the Discrete Factor Random Effects method to control for unobserved heterogeneity with four permanent and two time-varying mass points.

The majority of marginal effects calculated from the model that does not control for unobserved heterogeneity (Model 1) are dampened compared to the model that uses the Discrete Factor Random Effects method (Model 2). Thus, neglecting to control for unobserved differences would result in an overestimation of the impact of a moderate disability on employment outcomes. This finding supports the justification hypothesis of disability reporting. Conversely, the majority of marginal effects of a severe disability are magnified. This result is compatible with the stigma effect in reporting a disability. As the moderately and severely disabled have been shown to be distinct groups, it is highly plausible that they would face different motivations in reporting disability.

The preferred model in Table 6.2 shows that individuals with a moderate disability are over 2.5 percentage points less likely to be employed than non-disabled individuals and those

Table 6.2: Marginal Effects of Disability on Employment Outcomes

Variable	Moderate Disability				Severe Disability			
	Model 1		Model 2		Model 1		Model 2	
Employment Rate (%)	-2.71	***	-2.53	***	-35.0	***	-36.7	***
	(1.10)		(0.77)		(2.84)		(2.72)	
Log Wage	-0.12	***	-0.02	*	-0.09	**	-0.21	***
	(0.01)		(0.01)		(0.05)		(0.03)	
No Change (%)	-5.20	***	-4.51	***	-12.6	***	-12.8	***
	(0.88)		(1.00)		(2.36)		(2.65)	
Jobless (%)	1.93	***	2.02	***	12.2	***	12.9	***
	(0.33)		(0.31)		(1.38)		(1.29)	
Change Occupation (%)	1.77	***	1.39	**	2.72	*	2.25	
	(0.69)		(0.68)		(1.92)		(1.86)	
Change Employer (%)	1.04	**	0.84	*	-2.10	***	-2.25	***
	(0.61)		(0.54)		(0.61)		(0.72)	
Change Both (%)	0.45		0.27		-0.24		-0.11	
	(0.27)		(0.30)		(0.31)		(0.64)	

Note: Bootstrapped standard errors are in parentheses.

Model 1 = Model without controlling for unobserved heterogeneity

Model 2 = Model with 4 permanent and 2 time-varying mass points to account for unobserved heterogneity

*** indicates significance at the 1% level, ** 5% level, * 10% level who are employed have a slightly lower wage rate. These moderately disabled workers are over 4.5 percentage points less likely to remain employed at their current job and over two percentage points more likely to become jobless compared to a worker without a disability. Moderately disabled workers are about 1.4 percentage points more likely to remain employed and change occupations and 0.8 percentage points more likely to change employers. In all, disabled workers are 2.5 percentage points more likely to change occupations, employers, or both compared to non-disabled workers. As 10.76 percent of non-disabled workers make these transitions, this implies that moderately disabled workers are 23 percent more likely to make an employment transition.

The last two columns of Table 6.2 are quite different from the first two columns, again illustrating the difference between the moderately and severely disabled. The preferred model shows that the severely disabled who are currently employed are 37 percentage points less likely to remain employed than non-disabled workers and also earn a significantly lower wage. Overall, these workers are almost 13 percentage points less likely to remain with their current job. A large portion of those who leave their current job become non-employed. Still, severely disabled workers are 2.3 percent more likely to remain employed and change occupations compared to non-disabled workers. On the other hand, severely disabled workers are also 2.3 percent less likely to change employers. Workers with a severe disability may be physically incapable of continuing in their line of work and have no choice but to change occupations if they wish to remain employed. However, those who are able to may prefer to stay with their same employer so as not to lose health benefits and avoid potential hiring discrimination.

As it has been established that disabled individuals are less likely to remain in their current job and thus have lower tenure, the effects of occupational and employer tenure on wages are now considered. Table 6.3 contains estimates of the marginal effects of tenure on log wages. The first column contains estimates from Model 1, which does not control for unobserved heterogeneity. The second column contains estimates from Model 2, which controls for unobserved heterogeneity. Model 1 predicts that for a disabled worker an additional year of occupational tenure will add 0.006 and an additional year of employer tenure will add 0.011 to log wages.

Model 2, the preferred model, predicts that for disabled workers additional years of occupational and employer tenure will add 0.001 and 0.008 to log wages, respectively. Thus, without controls for unobserved heterogeneity, the impact of tenure on wages is over predicted.

The effects of tenure from the preferred model (Model 2) are presented in the second column of Table 6.3. Occupational tenure increases log wage by 0.002, which translates to about a 2 cent increase in wages for each year of tenure. Employer tenure has an even larger effect, increasing log wages by 0.011, or about 10 cents. The squared terms for both types of tenure indicate that tenure increases wages at a decreasing rate. The effects of occupational and employer tenure on wages are smaller for disabled workers, although the effect for occupational tenure is not statistically significant. Reasons for the smaller role of tenure could include discrimination, lack of training received by disabled workers, or productivity differences compared to non-disabled workers that accumulate each year. Overall, tenure still has a positive effect on wages for disabled workers.

Table 6.3: Marginal Effects of Tenure on Log Wages

Variable	Model 1		Model 2	
Occupational Tenure	0.007	***	0.002	***
Occupational Tenure Squared/100	-0.004	**	-0.005	**
Occupational Tenure*Disability	-0.001	*	-0.001	
Employer Tenure	0.013	***	0.011	***
Employer Tenure Squared/100	-0.018	***	-0.030	***
Employer Tenure*Disability	-0.002	***	-0.003	***

Note: *** indicates significance at the 1% level, ** 5% level, * 10% level
Model 1 = Model without controlling for unobserved heterogeneity
Model 2 = Model with 4 permanent and 2 time-varying mass points

Dynamic Effects

While per period marginal effects are a good starting point for discerning the impact of disability on employment outcomes, they do not capture the dynamics of the model. Simulations are conducted to analyze the marginal effects over time. In the first set of simulations, individuals are simulated to be non-disabled. Next, individuals are simulated to become moderately disabled starting in the second wave and remain disabled. The same simulation is then conducted for severely disabled individuals. All groups are simulated to remain employed with their current employer in their current occupation. The simulated hourly wages earned by each group are then graphed, and are contained in Figure 6.1. Log wages are retransformed to dollars using a smearing factor.[1]

The impact of a disability on wages, holding employment transitions constant, is shown in Figure 6.1. The onset of disability is indicated in the graph as time "0". Following the onset of disability, there is a sharp decline in wages. This initial drop represents a 57 cent loss in wages for moderately disabled workers, and a \$1.36 loss for severely disabled workers. For a full time moderately or severely disabled worker, this is a loss of about \$1,190 and \$2,804, respectively, in the first year of disability.[2] For both types of disability, the gap between own wages and the wages of non-disabled workers grows with length of time disabled. Thus, disability causes not only a loss in wages, but also a decline in the returns to experience.

In the next simulations, all individuals who are employed in wave one are simulated to be non-disabled, and then incur a disability starting in wave two (time "0"). From this point four different scenarios are considered. In the first scenario, workers are simulated to remain employed with their current employer in their current occupation for the remainder of the survey. In the second scenario, workers are simulated to change occupations in the second period and then remain in the same occupation. Next, workers are simulated to change employers in the second period, and finally workers are simulated to change both occupations and employers in the second period. The results are depicted in Figures 6.2 and 6.3.

Figure 6.2 shows the results when workers are simulated to have a moderate disability. Workers who remain in the same occupation with their same employer (or those who have "no change") serve as a comparison for the employment transitions.[3] The figure shows that changing occupations or employers significantly decreases the hourly wage rate of moderately

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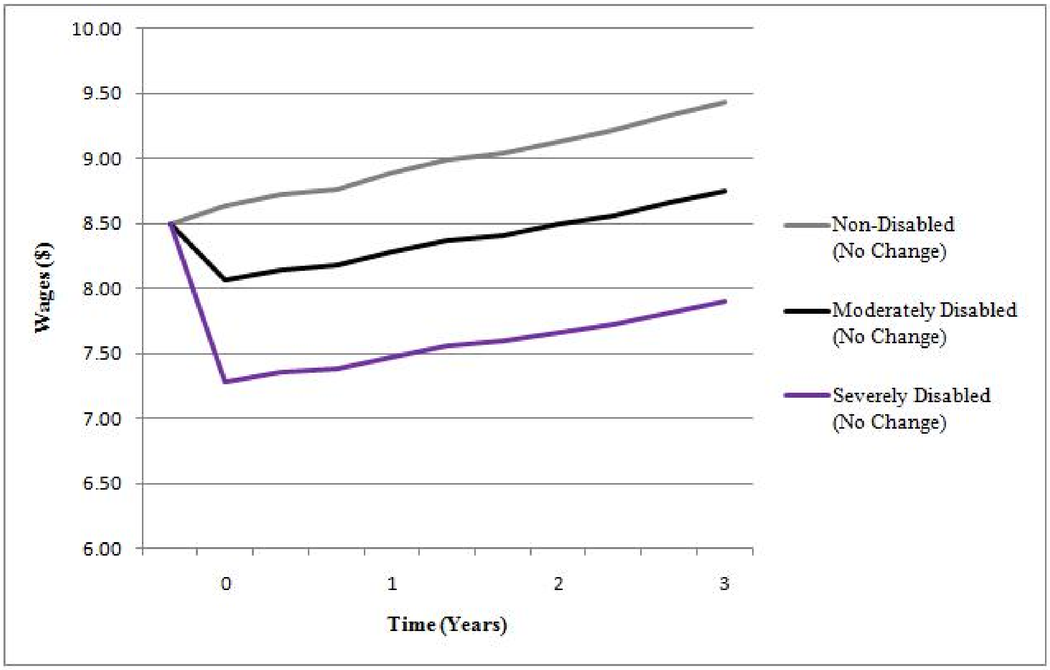
[1] Recall that $E[y] = e^{(X\beta)}e^{(0.5\sigma^2)}$. Thus, the homoskedastic smearing factor is calculated as $e^{(0.5\sigma^2)}$ and is multiplied by the retransformed wages.

[2] Yearly losses due to disability for three years following disability onset and for each employment transition are contained in Appendix Table A.1.

[3] In the first wave, the average person has 11.8 years of occupational tenure and 8.2 years of employer tenure.

Figure 6.1: Simulated Wages by Disability Status



disabled workers compared to those who stay with their job. In the period in which the transition is made, workers who change occupations or employers earn wages that are 14 or 19 cents lower, respectively, compared to those who remain in their same job. To put this drop in perspective, a worker with five years of employer tenure who changes employers will experience about the same drop in wages as if he lost one year of education. Workers who change both occupations and employers experience an even larger drop in wages. The gap between workers who do not change jobs and workers who change occupations widens over time, while the gap closes for those who change employers. The difference for moderately disabled workers who make either transition is still statistically significant three years following the transition.[4] These results are suggestive of a significant loss of wages from changing occupations and/or changing employers that perpetuates for at least three years. Further, occupational changes appear to have a more detrimental long-term affect than employer changes.

[4]95 percent confidence intervals around the simulated wages are contained in Appendix Tables A.2 and A.3.

Figure 6.2: Simulated Wages of Moderately Disabled Workers

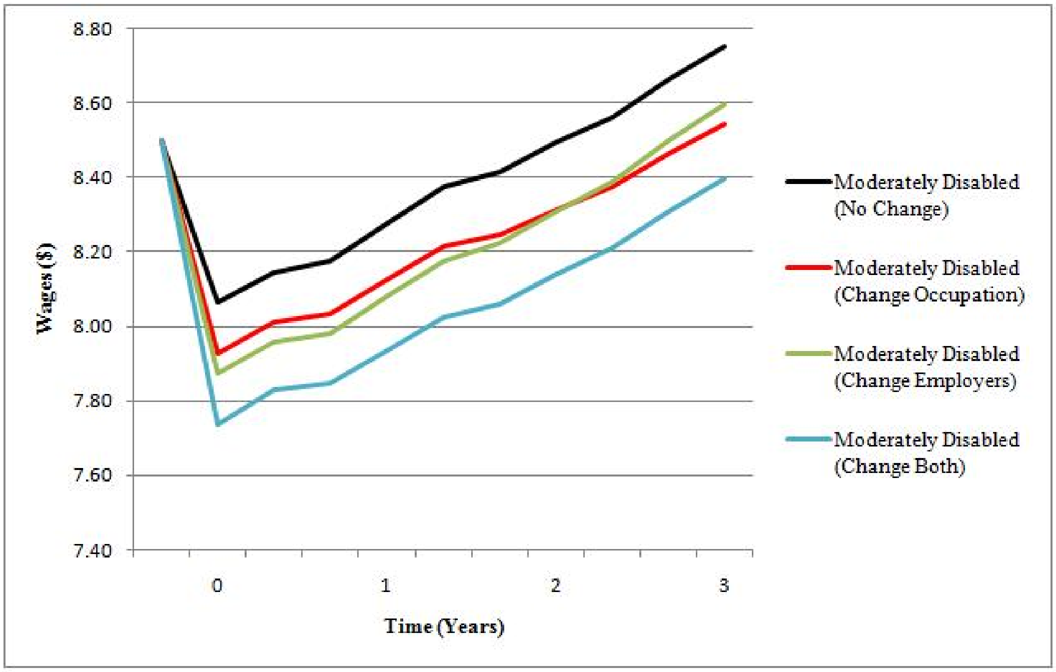
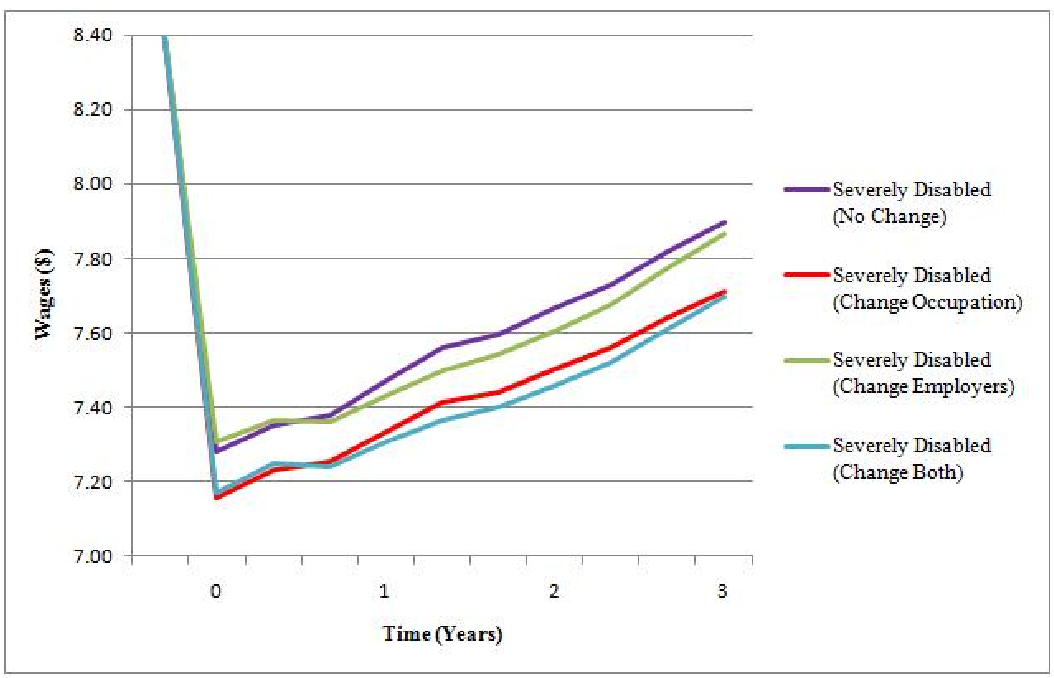


Figure 6.3: Simulated Wages of Severely Disabled Workers



Simulated wages across time for severely disabled workers are depicted in Figure 6.3. Similar to moderately disabled workers, severely disabled workers who change occupations experience a significant drop in wage. The initial decline in wages is about 13 cents, and the difference between occupation-changers and those without a transition increases to 19 cents after three years. However, the effect of changing employers is not statistically significant. Recall, though, that severely disabled workers are less likely to change employers compared to non-disabled individuals. The finding that tenure has a smaller effect on wages for individuals who are more severely disabled is consistent with previous findings regarding returns to education and human capital. The smaller effect can be explained by both differences in real returns from tenure (i.e. training, etc.) or discrimination. Overall, the results still suggest that severely disabled workers are adversely affected by changing occupations.

6.2 Occupational Characteristics

In this section, I present the results from the joint estimation of equations for employment, occupational choice, wages, disability status, initial disability status, and attrition. I present estimates where I have not controlled for unobserved heterogeneity, referred to as Model 1, and where I have used the Discrete Factor Random Effects Method with four permanent mass points to control for permanent unobserved heterogeneity, referred to as Model 2.[5] The second model is the preferred model, as it reduces bias caused by unobservables across equations. The predictions from this model are compared to actual sample proportions in Table 6.4, to gauge the fit of the model. The predictions for disability status, employment rate, and occupational characteristics are all very similar to the actual proportions, suggesting that the model is accurate.

Marginal Effects

[5]Note that in the analysis of the previous section, four permanent and two time-varying mass points were used, whereas here there is no time-varying heterogeneity. The number of mass points is determined by adding mass points until the likelihood function fails to significantly improve, and thus may vary across models. In this model, adding time-varying heterogeneity did not improve the fit of the model.

Table 6.4: Predicted Values: Occupational Choice

Variable	Actual	Predicted
Moderately Disabled	0.039	0.039
Severely Disabled	0.067	0.067
Employment Rate	0.887	0.889
Data	0.49	0.48
People	0.57	0.62
Things	0.46	0.46
Reasoning	0.61	0.62
Math	0.62	0.63
Language	0.43	0.47
SVP	0.52	0.51
Strength	0.37	0.37
Ln(Wage) ($E_t = 1$)	2.17	2.18

The marginal effects of disability on employment rates and occupational choice are presented in Table 6.5. Marginal effects are calculated for both moderate and severe disabilities, in reference to non-disabled individuals. Model 1, which does not control for unobserved heterogeneity, produces larger estimates than Model 2, which controls for permanent unobserved heterogeneity. This suggests that treating all variables as exogenous produces inflated estimates.

The calculated marginal effects from the Discrete Factor Random Effects Method (Model 2) reveal that moderately disabled individuals are slightly less likely to be employed and severely disabled individuals are significantly less likely to be employed compared to non-disabled individuals.[6] The results also reveal that conditional on employment, there is selection into occupations by disability status. Moderately and severely disabled workers are less likely to select occupations with high skill requirements, with the exception of strength. Workers with any degree of disability are least likely to choose occupations that require a high amount of reasoning, math, or training (SVP). Many of the occupations that have high strength requirements have low requirements for the other characteristics. That disabled workers are employed in low skill jobs with high physical requirements may be representative of the lack

[6] Note that in this analysis, unlike in the previous section where employment was estimated separately for the employed and jobless, only one employment equation is estimated.

Table 6.5: Marginal Effects of Disability on Occupational Choice

Variable	Moderate Disability				Severe Disability			
	Model 1		Model 2		Model 1		Model 2	
Employment Rate	-0.50	**	-0.47	**	-6.67	***	-6.73	***
	(0.24)		(0.23)		(0.38)		(0.32)	
Data	-7.54	***	-2.69	***	-3.78	***	-1.54	**
	(1.39)		(0.90)		(0.85)		(0.84)	
People	-4.93	***	-1.22	*	-3.04	***	-0.82	*
	(0.99)		(0.87)		(0.81)		(0.57)	
Things	-4.47	***	-3.06	***	-3.53	***	-2.12	***
	(1.09)		(0.77)		(1.01)		(0.53)	
Reasoning	-9.83	***	-6.25	***	-4.97	***	-3.08	***
	(1.42)		(1.51)		(0.91)		(0.93)	
Math	-8.91	***	-5.50	***	-4.98	***	-2.96	***
	(1.44)		(1.42)		(0.96)		(0.92)	
Language	-6.79	***	-3.01	***	-3.73	***	-1.51	**
	(1.26)		(1.03)		(0.93)		(0.70)	
SVP	-11.58	***	-5.36	***	-6.11	***	-3.16	***
	(1.87)		(1.35)		(1.18)		(1.03)	
Strength	1.81	**	0.94		0.20		0.08	
	(1.04)		(1.22)		(0.82)		(0.73)	

Note: Bootstrapped standard deviations are in parentheses.

Model 1 = Model without controlling for unobserved heterogeneity

Model 2 = Model with 4 permanent mass points to account for permanent unobserved heterogneity

*** indicates significance at the 1% level, ** 5% level, * 10% level

of opportunities available to this group. The notion that there are barriers to certain types of employment is an important piece of the employment puzzle regarding disabled individuals.

Table 6.5 also shows that moderately disabled workers are less likely than severely disabled workers to be employed in occupations with any of the non-physical characteristics. As many severe disabilities are physical limitations, these workers may have adapted to their disability by improving their mental skills. However, note that very few severely disabled individuals are employed, so the results for the severely disabled are not as robust as for the moderately disabled.

Having controlled for non-random selection into occupations, I now interpret the impact of occupational characteristics on both disability status and wages. Table 6.6 contains the results for the marginal effects of the characteristics on disability status. The majority of the

Table 6.6: Marginal Effects of Occupational Characteristics on Disability

Variable	Moderate Disability		Severe Disability	
Data	0.27		-0.11	
	(0.22)		(0.27)	
People	-0.41	***	0.27	***
	(0.15)		(0.11)	
Things	-0.30	**	0.11	
	(0.14)		(0.11)	
Reasoning	-0.32		-0.02	
	(0.27)		(0.18)	
Math	0.11		-0.04	
	(0.18)		(0.19)	
Language	-0.30	**	0.32	**
	(0.18)		(0.18)	
SVP	-0.03		-0.24	
	(0.21)		(0.28)	
Strength	-0.27	***	0.28	***
	(0.13)		(0.09)	

Note: Bootstrapped standard deviations are in parentheses.
Model with 4 permanent mass points to account for permanent unobserved heterogeneity
*** indicates significance at the 1% level, ** 5% level, * 10% level

marginal effects are small, less than one percentage point. Although small, occupations that require working with people, things, reasoning, language, training, and strength decrease the probability of having a moderate disability, whereas working with data and math increase the odds of a moderate impairment. Occupations that have all of these characteristics include technicians, inspectors, storekeepers, and utility workers. Although these jobs do not require high amounts of strength, they are very active, hands-on jobs, and likely have a higher incidence of work related injuries than desk jobs. Occupations that require work with people, things, language, and strength, but don't require work with data, reasoning, math, and training have a higher probability of causing a severe disability. Examples of such occupations are professional athletes, drivers, performers, and physical therapy aides. Workers in these professions are more likely to be faced with severe work-related accidents, such as back injuries and paralysis.

Table 6.7 describes the marginal effects of occupational characteristics on log wages for disabled workers. Working with data, people, things, reasoning, math, language, and strength

Table 6.7: Marginal Effects of Occupational Characteristics on Wages of Disabled Workers

Variable	Log Wages	
Data	0.055	**
	(0.029)	
People	0.054	**
	(0.029)	
Things	0.097	***
	(0.020)	
Reasoning	0.078	**
	(0.044)	
Math	0.107	***
	(0.029)	
Language	0.086	**
	(0.038)	
SVP	-0.019	
	(0.029)	
Strength	0.071	***
	(0.028)	

Note: Bootstrapped standard deviations are in parentheses.
Model with 4 permanent mass points to account for permanent unobserved heterogeneity
*** indicates significance at the 1% level, ** 5% level, * 10% level

all contribute positively to earned wages. The characteristics with the largest return to wages are math and things (inanimate objects). However, specific vocational preparation accrued by disabled workers does not positively affect wages. This could be indicative that training has a smaller impact on disabled workers, or that employers discriminate against disabled workers and don't value their training, as training is found to positively impact the wages of non-disabled workers.

Table 6.8: Marginal Effects of Occupational Characteristics on Wages, By Model

Variable	Log Wages			
	Employment Transitions Model		Occupational Choice Model	
Data	0.068	***	0.055	**
	(0.024)		(0.029)	
People	0.121	***	0.054	**
	(0.027)		(0.029)	
Things	0.065	***	0.097	***
	(0.015)		(0.020)	
Reasoning	0.085	**	0.078	**
	(0.040)		(0.044)	
Math	0.035		0.107	***
	(0.036)		(0.029)	
Language	0.082	***	0.086	**
	(0.022)		(0.038)	
SVP	0.008		-0.019	
	(0.024)		(0.029)	
Strength	0.079	**	0.071	***
	(0.025)		(0.028)	

Note: Bootstrapped standard deviations are in parentheses.
*** indicates significance at the 1% level, ** 5% level, * 10% level

6.3 Comparison Across Models

The previous sections describe the results from two models: one focused on the presence and effect of employment transitions, and the other on occupational choice and characteristics. Both analyses estimate wage equations, the second analysis doing so more precisely, having controlled for occupational choice. The first analysis used occupational dummies to control for occupation; here I have replaced those dummies with occupational characteristics so that both analyses estimate the wage equation with the same control variables. Table 6.8 compares the results of these two wage equations. The results suggest that the effect of data, people, reasoning, SVP, and strength were all overestimated in the analysis that did not control for occupational choice. The effects of things, math, and language, on the other hand, were all underestimated. These differences highlight the importance of controlling for occupational choice, particularly if characteristics of that choice are thought to impact other variables.

Chapter 7

Conclusion

In this research, I estimate the direct impact of disability on employment outcomes and the indirect impact of disability on wages via tenure implied by these occupational and employer transitions. I also measure the effect of disability on occupational choice, and the effect characteristics implied by this choice have on disability status and wages. Using the Survey of Income and Program Participation and the Dictionary of Occupational Titles, I estimate two dynamic models of disability and employment controlling for permanent and time-varying unobserved heterogeneity.

The results of the first analysis suggest that workers with either a moderate or severe disability are more likely to change occupations or employers, with the exception that severely disabled workers are less likely to change employers. Specifically, moderately disabled workers are 23 percent more likely to change occupations and/or employers compared to non-disabled workers. Previous literature on disability and employment outcomes generally consider "job change" as a change in employers, and this research illustrates the role of occupational change in these transitions. Further, the importance of controlling for unobserved characteristics is shown, as estimates of the impact of disability on employment outcomes differ depending on whether or not one controls for unobserved individual characteristics.

The first analysis also shows the effect of occupational and employer tenure on wages. Simulating potential employment paths for disabled workers, I find that for moderately disabled workers, changing occupations is associated with an immediate 14 cent wage loss and changing employers causes an immediate 19 cent wage loss for moderately disabled workers. Thus, moderately disabled workers who respond to their disability by changing employers and/or occupations help explain a significant portion of the wage gap between disabled and non-disabled workers.

The second analysis finds that disabled workers select occupations differently than non-disabled workers. Workers with a disability have lower requirement levels of all characteristics, with the exception of strength. The tasks required by these different occupations are found to have different effects on disability status and wages. Many occupational characteristics have different marginal effects on moderate and severe disabilities. Jobs with high data and low work with people and things, such as technicians, cause moderate disabilities, whereas jobs with high requirements in things and strength and low requirements in training, such as professional athletes, cause severe disabilities. Seven of the eight occupational characteristics have a positive impact on wages for disabled workers. Estimates of characteristics on wages are more precise in this second analysis, which controls for occupational choice, than the first analysis.

This dissertation work suggests that there may be barriers to keeping one's job upon becoming disabled as well as entry into certain occupations for disabled individuals. Historically, disabled workers have faced many barriers to employment, promotions, and equal pay. The Americans with Disabilities Act (ADA) took great strides to change this, requiring firms to provide "reasonable accommodations" to disabled workers in an attempt to minimize the amount of job turnover experienced by disabled workers. This research supports the goal of the ADA, as changing occupations and employers is found to negatively impact wages. Stricter requirements added to legislation like the ADA could help lower the transition rates among this group and provide a better employment outlook for disabled workers. Specific changes could include extending the ADA to cover all employers or government subsidies for accommodations.[1] Other programs, such as occupation-specific vocational rehabilitation, could also aid in reducing transitions. Barriers to entry into certain occupations may result from disabled individual being underqualified for these positions. The lack of qualification may come from

[1]The ADA currently only covers firms with 15 or more employees

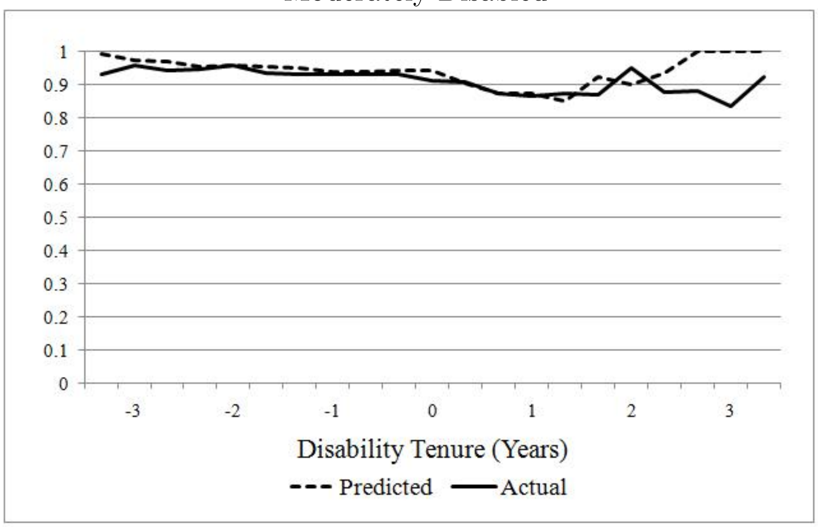
difficulties receiving training or education. Legislation such as the Individuals with Disabilities Education Act (IDEA) may help to combat any qualification differences by disability status encountered early on. IDEA requires states receiving federal money related to the legislation provide disabled students individualized attention in the classroom to suit the students' needs. IDEA explicitly covers individuals under the age of 21; accordingly a mechanism to help individuals who become disabled later in life would also likely be beneficial.

Appendix A

Supplemental Graphs

Figure A.1: Model Fit - Employment Rate by Disability Tenure

Moderately Disabled



Severely Disabled

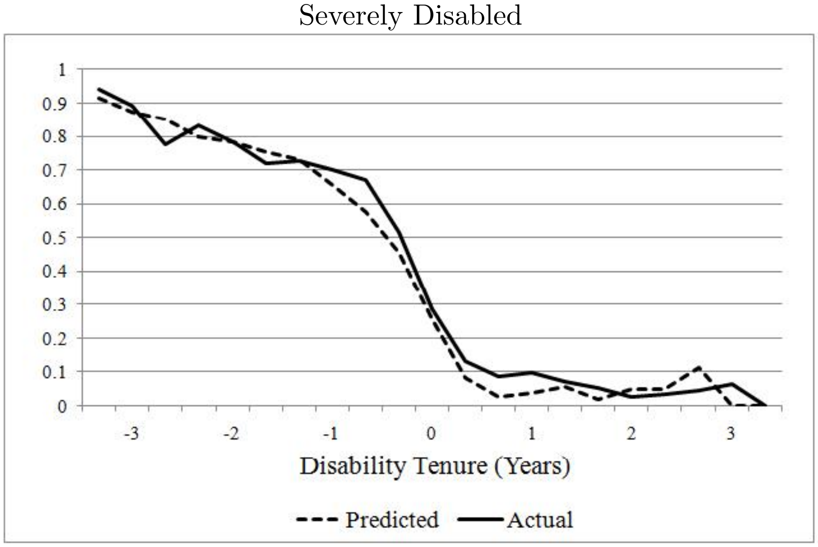


Figure A.2: Simulated Wages - Moderately Disabled

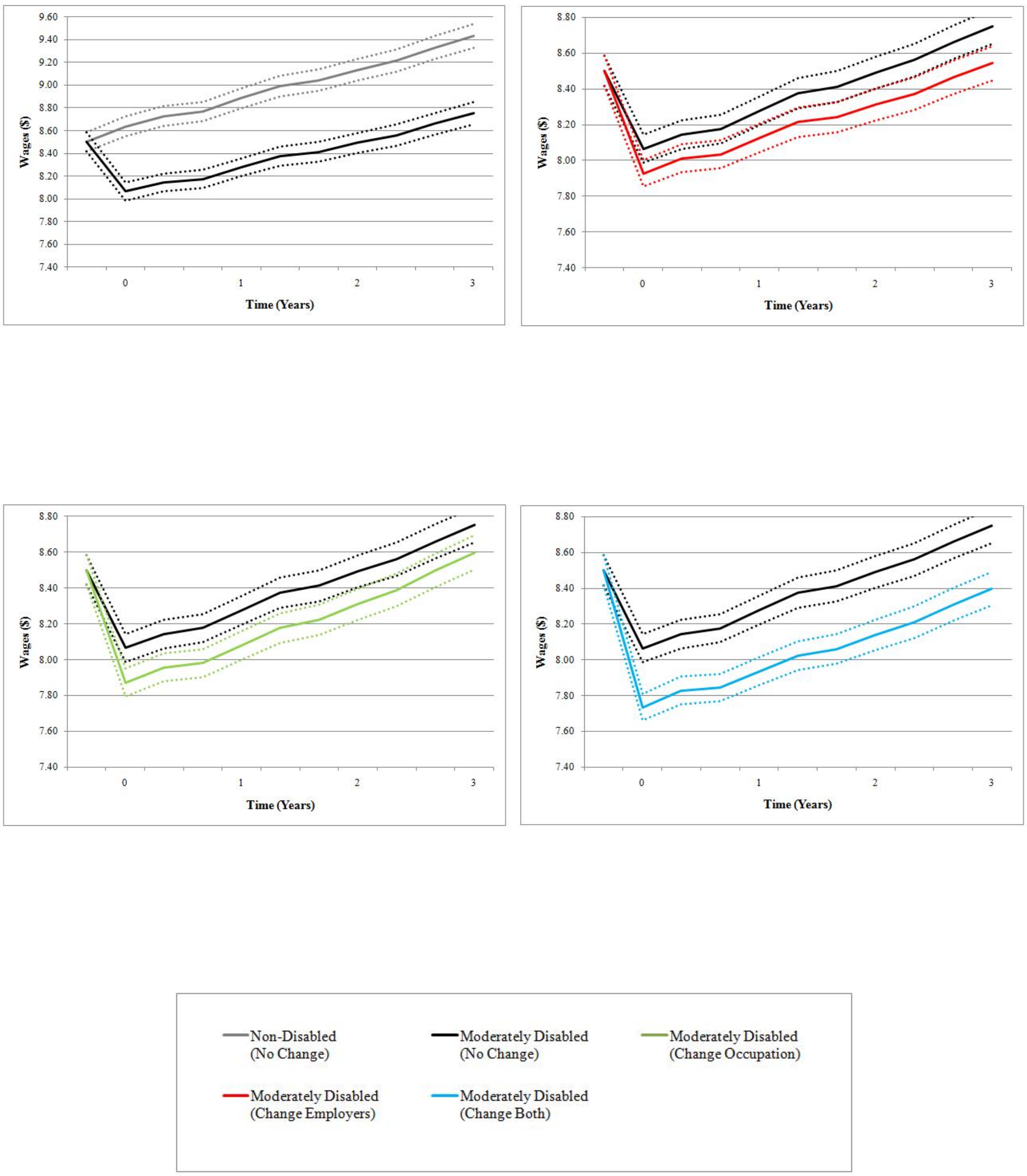


Figure A.3: Simulated Wages - Severely Disabled

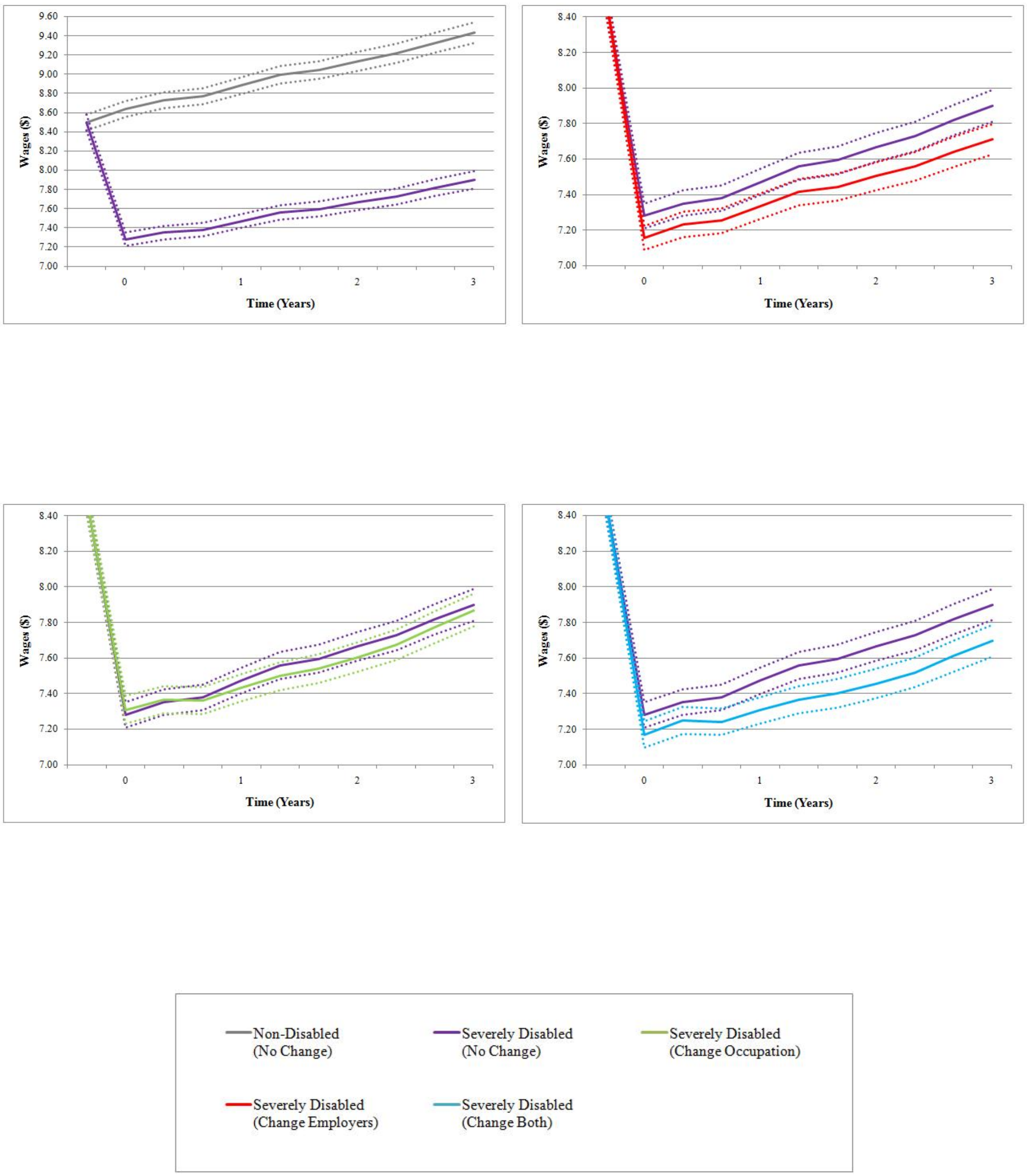


Table A.1: Yearly Losses
(in 2010 $)

Variable	Year One	Year Two	Year Three
Moderate Disability	1,575	1,670	1,769
For a moderately disabled worker:			
Change Occupation	375	437	513
Change Employers	522	533	469
Change Both	897	970	982
Severe Disability	3,712	3,866	4,022
For a severely disabled worker:			
Change Occupation	339	395	464
Change Employer	-22	139	144
Change Both	317	534	608

Appendix B

Coefficient Estimates

B.1 Employment Transitions

Table B.1: Coefficient Estimates from Disability Equation (Employment Transitions Model)
(Jointly Estimated with Employment, Wage, Attrition, and Initial Variables Equations)

Variable	Moderately Disabled		Severely Disabled	
Age	0.20	(0.12)	-0.44	(0.23)
Age Squared/100	-0.34	(0.29)	1.38	(0.54)
Age Cubed/1000	0.02	(0.02)	-0.12	(0.04)
Non-White	-0.06	(0.05)	-0.01	(0.08)
Unmarried	0.15	(0.04)	0.28	(0.07)
Number of Children	-0.06	(0.02)	-0.04	(0.03)
Education				
Less than High School	0.13	(0.06)	0.34	(0.08)
Some College	-0.08	(0.04)	-0.35	(0.08)
College	-0.47	(0.07)	-1.21	(0.13)
More than College	-0.59	(0.09)	-1.63	(0.20)
Region				
North East	-0.11	(0.05)	-0.09	(0.09)
Mid West	-0.09	(0.05)	-0.03	(0.08)
West	0.00	(0.05)	-0.10	(0.08)
Non-metropolitan	0.09	(0.04)	-0.00	(0.08)
Disabled$_{t-1}$	3.36	(0.07)	2.07	(0.14)
Severely Disabled$_{t-1}$	-0.69	(0.12)	1.85	(0.14)
For those who did not enter the survey disabled				
Time Disabled$_{t-1}$	1.04	(0.12)	1.24	(0.27)
Time Disabled Squared$_{t-1}$	-0.19	(0.05)	-0.20	(0.11)
Time Disabled Cubed$_{t-1}$/10	0.12	(0.05)	0.12	(0.10)
Time Disabled$_{t-1}$*Severe$_{t-1}$	-0.08	(0.03)	-0.07	(0.03)
Time Disabled Squared$_{t-1}$*Severe$_{t-1}$	0.02	(0.01)	0.02	(0.01)
Time Disabled Cubed$_{t-1}$*Severe$_{t-1}$/10	-0.01	(0.01)	-0.01	(0.01)
Enter the survey disabled	0.36	(0.11)	1.35	(0.15)

Table B.1 (Continued)

Variable	Moderately Disabled		Severely Disabled	
For those who entered the survey disabled				
Total Time Disabled$_{t-1}$	0.36	(0.04)	0.33	(0.04)
Total Time Disabled Squared$_{t-1}$/10	-0.19	(0.03)	-0.18	(0.03)
Total Time Disabled Cubed$_{t-1}$/100	0.03	(0.00)	0.03	(0.01)
Total Time Disabled$_{t-1}$*Severe$_{t-1}$	-0.00	(0.00)	-0.00	(0.00)
Total Time Disabled Missing$_{t-1}$	-0.53	(0.09)	-0.43	(0.13)
Health Insurance$_{t-1}$	-0.28	(0.05)	-0.41	(0.07)
Non-employed	-1.15	(0.15)	4.36	(0.40)
Hours Worked	-0.05	(0.01)	0.05	(0.02)
Hours Worked Squared/100	0.03	(0.01)	-0.08	(0.02)
Small Employer (<25 Employees)	-0.07	(0.05)	-0.25	(0.18)
Small Employer*Disability$_{t-1}$	0.01	(0.09)	0.25	(0.22)
Medium Employer (25-99 Employees)	-0.17	(0.06)	-0.18	(0.20)
Medium Employer*Disability$_{t-1}$	0.07	(0.10)	-0.57	(0.30)
Employer Size Missing	-0.01	(0.30)	0.87	(0.40)
Occupational Category 1	0.21	(0.10)	0.29	(0.37)
Occupational Category 2	0.18	(0.08)	-0.22	(0.28)
Occupational Category 3	0.41	(0.09)	0.28	(0.29)
Occupational Category 4	0.13	(0.08)	0.25	(0.24)
Occupational Category 5	0.11	(0.08)	0.03	(0.25)
Occupational Category 6	0.27	(0.10)	0.11	(0.36)
Occupational Category 7	0.25	(0.09)	-0.45	(0.31)
Occupational Category 8	0.41	(0.07)	0.19	(0.23)
Occupational Tenure	-0.00	(0.00)	-0.00	(0.01)
Employer Tenure	0.00	(0.00)	-0.11	(0.02)
Unearned Income	0.48	(0.04)	0.51	(0.05)

Notes: Standard deviations in parentheses. The omitted category is non-disabled. Month and Year Dummies were also regressors but are not shown in the above table. Estimates of permanent and time-varying heterogeneity are available in Table B.5.

Table B.2: Coefficient Estimates from Employment Equation for the Employed (Employment Transitions Model)
(Jointly Estimated with Disability, Wage, Attrition, and Initial Variables Equations)

Variable	Become Jobless		Change Occupation		Change Employer		Change Both	
Age	0.18	(0.17)	0.17	(0.08)	0.19	(0.09)	-0.22	(0.29)
Age Squared/100	-0.53	(0.40)	-0.48	(0.19)	-0.52	(0.22)	0.51	(0.74)
Age Cubed/1000	0.05	(0.03)	0.04	(0.02)	0.04	(0.02)	-0.04	(0.06)
Non-White	0.54	(0.06)	-0.01	(0.03)	-0.04	(0.05)	-0.19	(0.12)
Unmarried	0.56	(0.06)	0.07	(0.03)	0.17	(0.04)	0.55	(0.09)
Number of Children	0.06	(0.02)	-0.00	(0.01)	0.00	(0.02)	0.05	(0.04)
Education								
Less than High School	0.32	(0.07)	-0.13	(0.04)	0.10	(0.05)	-0.14	(0.13)
Some College	-0.17	(0.06)	0.05	(0.03)	-0.01	(0.04)	-0.02	(0.10)
College	-0.40	(0.07)	0.06	(0.03)	-0.22	(0.05)	-0.39	(0.13)
More than College	-0.72	(0.11)	-0.13	(0.05)	-0.49	(0.07)	-0.79	(0.20)
Region								
North East	-0.02	(0.07)	-0.01	(0.04)	-0.04	(0.05)	-0.49	(0.13)
Mid West	-0.06	(0.07)	0.04	(0.03)	-0.04	(0.04)	-0.15	(0.10)
West	0.09	(0.06)	0.14	(0.03)	0.11	(0.04)	-0.10	(0.11)
Non-Metropolitan	0.16	(0.06)	0.01	(0.03)	0.07	(0.04)	0.22	(0.10)

Table B.2 (Continued)

Variable	Become Jobless		Change Occupation		Change Employer		Change Both	
Disabled	0.85	(0.13)	0.18	(0.10)	0.19	(0.13)	0.50	(0.26)
Severely Disabled	2.25	(0.17)	0.46	(0.25)	-0.77	(0.41)	-0.09	(0.58)
For those who did not enter the survey disabled								
Time Disabled	0.03	(0.23)	-0.31	(0.20)	0.16	(0.22)	-2.68	(1.62)
Time Disabled Squared	-0.04	(0.09)	0.11	(0.08)	-0.01	(0.08)	2.00	(1.46)
Time Disabled Cubed/10	0.03	(0.09)	-0.10	(0.08)	-0.02	(0.08)	-3.81	(3.17)
Enter the survey disabled	0.10	(0.22)	-0.14	(0.18)	0.41	(0.21)	-0.34	(0.43)
For those who entered the survey disabled								
Total Time Disabled	-0.04	(0.07)	-0.02	(0.06)	0.03	(0.06)	-0.14	(0.17)
Total Time Disabled Squared/10	-0.02	(0.05)	0.01	(0.04)	-0.08	(0.04)	0.10	(0.13)
Total Time Disabled Cubed/100	0.01	(0.01)	-0.00	(0.01)	0.02	(0.01)	-0.02	(0.03)
Total Time Disabled*Severe	0.01	(0.00)	0.01	(0.00)	0.01	(0.01)	0.01	(0.01)
Total Time Disabled Missing	-0.27	(0.19)	-0.07	(0.16)	-0.39	(0.19)	0.42	(0.38)
Union$_{t-1}$	-0.14	(0.07)	-0.29	(0.04)	-0.25	(0.05)	-0.30	(0.15)
Occupational Tenure$_{t-1}$	0.06	(0.02)	-0.06	(0.01)	-0.09	(0.01)	-0.08	(0.04)
Occupational Tenure Squared$_{t-1}$/100	-0.42	(0.14)	0.21	(0.08)	0.51	(0.10)	0.38	(0.30)
Occupational Tenure Cubed $_{t-1}$/1000	0.09	(0.03)	-0.03	(0.02)	-0.07	(0.02)	-0.04	(0.06)
Disability*Occupational Tenure$_{t-1}$	-0.00	(0.01)	0.00	(0.01)	0.01	(0.01)	0.01	(0.02)
Occupational Tenure Missing $_{t-1}$	0.16	(0.09)	-0.26	(0.05)	-0.32	(0.07)	-0.64	(0.18)
Employer Tenure$_{t-1}$	-0.85	(0.03)	-0.41	(0.01)	-0.27	(0.01)	-1.03	(0.05)
Employer Tenure Squared$_{t-1}$/100	5.74	(0.23)	2.87	(0.10)	1.20	(0.11)	6.78	(0.52)
Employer Tenure Cubed$_{t-1}$/1000	-1.06	(0.06)	-0.55	(0.02)	-0.15	(0.02)	-1.23	(0.14)
Disability*Employer Tenure$_{t-1}$	0.02	(0.01)	0.02	(0.01)	0.00	(0.01)	0.00	(0.03)
Local Unemployment Rate	0.05	(0.01)	-0.03	(0.01)	0.00	(0.01)	0.02	(0.03)
Unearned Income	1.25	(0.05)	0.06	(0.05)	0.76	(0.04)	0.78	(0.12)

Notes: Standard deviations in parentheses. The omitted category is remaining with same occupation and employer.
Month and Year Dummies were also regressors but are not shown in the above table.
Estimates of permanent and time-varying heterogeneity are available in Table B.5.

Table B.3: Coefficient Estimates from Employment Equation for the Non-employed (Employment Transitions Model)
(Jointly Estimated with Disability, Wage, Attrition, and Initial Variables Equations)

Variable	Become Employed	
Age	-0.29	(0.19)
Age Squared/100	0.83	(0.47)
Age Cubed/1000	-0.08	(0.04)
Non-White	-0.36	(0.07)
Unmarried	-0.13	(0.07)
Number of Children	0.02	(0.03)
Education		
Less than High School	-0.11	(0.08)
Some College	0.08	(0.07)
College	0.09	(0.10)
More than College	0.46	(0.13)
Region		
North East	0.26	(0.08)
Mid West	0.28	(0.08)
West	0.31	(0.08)
Non-Metropolitan	-0.01	(0.07)
Disabled	0.30	(0.17)
Severely Disabled	-1.58	(0.18)
For those who did not enter the survey disabled		
Time Disabled	-0.99	(0.44)
Time Disabled Squared	0.41	(0.19)
Time Disabled Cubed/10	-0.38	(0.20)
Severe Disability*Time Disabled	0.03	(0.05)
Severe Disability*Time Disabled Squared	-0.02	(0.02)
Severe Disability*Time Disabled Cubed/10	0.02	(0.02)
Enter the survey disabled	-0.39	(0.20)
For those who entered the survey disabled		
Total Time Disabled	-0.18	(0.06)
Total Time Disabled Squared/10	0.12	(0.04)
Total Time Disabled Cubed/100	-0.02	(0.01)
Total Time Disabled*Severe	-0.00	(0.00)
Total Time Disabled Missing	0.16	(0.17)
Time Non-employed$_{t-1}$	-0.32	(0.02)
Local Unemployment Rate	-0.02	(0.02)
Unearned Income	-0.58	(0.08)

Notes: Standard deviations in parentheses.
Month and Year Dummies were also regressors but are not shown in the above table.
Estimates of permanent and time-varying heterogeneity are available in Table B.5.

Table B.4: Coefficient Estimates from Wage Equation (Employment Transitions Model)
(Jointly Estimated with Employment, Disability, Attrition, and Initial Variables Equations)

Variable	Wage	
Age	0.12	(0.02)
Age Squared/100	-0.22	(0.04)
Age Cubed/1000	0.01	(0.00)
Non-White	-0.13	(0.01)
Unmarried	-0.09	(0.01)
Number of Children	0.01	(0.00)
Education		
Less than High School	-0.19	(0.01)
Some College	0.10	(0.01)
College	0.32	(0.01)
More than College	0.46	(0.01)
Region		
North East	0.11	(0.01)
Mid West	0.02	(0.01)
West	0.09	(0.01)
Non-metropolitan	-0.11	(0.01)
Disabled	-0.02	(0.01)
Severely Disabled	-0.21	(0.03)
For those who did not enter the survey disabled		
Time Disabled	-0.04	(0.01)
Time Disabled Squared	0.01	(0.00)
Severe Disability*Time Disabled	0.02	(0.00)
Severe Disability*Time Disabled Squared	-0.00	(0.00)
Enter the survey disabled	0.01	(0.02)
For those who entered the survey disabled		
Total Time Disabled	-0.02	(0.01)
Total Time Disabled Squared/10	0.01	(0.01)
Total Time Disabled Cubed/100	-0.00	(0.00)
Total Time Disabled*Severe	0.00	(0.00)
Total Time Disabled Missing	0.02	(0.02)

Table B.4 (Continued)

Variable	Wage	
Hours Worked	-0.02	(0.00)
Hours Worked Squared/100	0.03	(0.00)
Hours Worked Cubed/1000	-0.00	(0.00)
Small Employer (<25 Employees)	-0.07	(0.00)
Small Employer*Disability$_{t-1}$	-0.03	(0.02)
Medium Employer (25-99 Employees)	-0.03	(0.00)
Medium Employer*Disability$_{t-1}$	-0.05	(0.02)
Employer Size Missing	-0.16	(0.03)
Occupational Category 1	-0.17	(0.01)
Occupational Category 2	-0.08	(0.01)
Occupational Category 3	-0.20	(0.01)
Occupational Category 4	-0.32	(0.01)
Occupational Category 5	-0.09	(0.01)
Occupational Category 6	-0.11	(0.01)
Occupational Category 7	-0.21	(0.01)
Occupational Category 8	-0.20	(0.01)
Employed$_{t-1}$	0.03	(0.01)
Occupational Tenure	0.00	(0.00)
Occupational Tenure Squared/100	-0.00	(0.00)
Occupational Tenure*Disability	-0.00	(0.00)
Employer Tenure	0.01	(0.00)
Employer Tenure Squared/100	-0.03	(0.00)
Employer Tenure*Disability	-0.00	(0.00)
Local Unemployment Rate	-0.00	(0.00)

Notes: Standard deviations in parentheses.
Month and Year Dummies were also regressors but are not shown in the above table.
Estimates of permanent and time-varying heterogeneity are available in Table B.5.

Table B.5: Unobserved Heterogeneity Parameters (Employment Transitions Model)

Point of Support	Probability Weight	Employment ($E_{t-1} = 1$) Become Jobless	Change Occupation	Change Employer	Change Both	Employment ($E_{t-1} = 0$)	Disability Moderate	Severe	Wages
Permanent									
1	0.10				Normalized to 0				
2	0.18	-0.92	-0.33	-0.55	-0.88	0.74	-0.30	0.38	1.32
		(0.11)	(0.05)	(0.07)	(0.23)	(0.14)	(0.08)	(0.15)	(0.01)
3	0.44	-0.65	-0.13	-0.28	-0.21	1.08	-0.44	0.94	0.90
		(0.08)	(0.04)	(0.06)	(0.15)	(0.09)	(0.07)	(0.10)	(0.01)
4	0.28	-0.40	0.09	-0.00	0.30	1.07	0.02	0.53	0.51
		(0.08)	(0.04)	(0.06)	(0.15)	(0.11)	(0.06)	(0.11)	(0.01)
Time-Varying									
1	0.98				Normalized to 0				
2	0.02	-30.8	0.41	2.22	0.99	2.13	-0.57	3.90	1.56
		(9.23)	(0.09)	(0.09)	(0.32)	(0.23)	(0.19)	(0.18)	(0.01)

Notes: Standard deviations in parentheses.

B.2 Occupational Choice

Table B.6: Conditional Coefficient Estimates from Occupational Choice Equation (Occupational Choice Model)
(Jointly Estimated with Employment, Wages,
Disability, Attrition, and Initial Variables Equations)

Variable	Employed	
Occupational Characterisics		
Data	0.04	(0.10)
Data*Disabled	0.05	(0.06)
People	-3.17	(0.09)
People*Disabled	0.01	(0.05)
Things	-1.30	(0.07)
Things*Disabled	-0.16	(0.04)
Reasoning	-1.46	(0.14)
Reasoning*Disabled	-0.11	(0.08)
Math	-0.40	(0.11)
Math*Disabled	-0.12	(0.07)
Language	-4.22	(0.12)
Language*Disabled	-0.04	(0.07)
SVP	0.95	(0.12)
SVP*Disabled	-0.19	(0.07)
Strength	1.34	(0.10)
Strength*Disabled	-0.03	(0.05)

Notes: Standard deviations in parentheses.
Unconditional parameters including age, marital status, urbanicity, education, number of children, disability status, and length of time disabled were also estimated, but are not shown in the above table.
Estimates of permanent heterogeneity are available in Table B.10.

Table B.7: Coefficient Estimates from Employment Equation (Occupational Choice Model) (Jointly Estimated with Occupational Choice, Wages, Disability, Attrition, and Initial Variables Equations)

Variable	Employed	
Age	-0.25	(0.07)
Age Squared/100	0.62	(0.18)
Age Cubed/1000	-0.05	(0.01)
Non-White	-0.56	(0.03)
Unmarried	-0.54	(0.03)
Number of Children	-0.02	(0.01)
Education		
Less than High School	-0.42	(0.04)
Some College	0.19	(0.03)
College	0.46	(0.04)
More than College	0.83	(0.06)
Region		
North East	0.01	(0.04)
Mid West	0.11	(0.03)
West	0.09	(0.03)
Non-Metropolitan	-0.05	(0.03)
Disabled	-0.07	(0.07)
Severely Disabled	-1.26	(0.08)
For those who did not enter the survey disabled		
Time Disabled	0.70	(0.08)
Time Disabled Squared	-0.80	(0.05)
Time Disabled Cubed/10	1.40	(0.05)
Severe Disability*Time Disabled	-0.17	(0.02)
Severe Disability*Time Disabled Squared	0.10	(0.01)
Severe Disability*Time Disabled Cubed/10	-0.15	(0.01)
Enter the survey disabled	-0.41	(0.07)
For those who entered the survey disabled		
Total Time Disabled	-0.12	(0.01)
Total Time Disabled Squared/10	0.15	(0.01)
Total Time Disabled Cubed/100	-0.03	(0.00)
Total Time Disabled*Severe	-0.01	(0.00)
Total Time Disabled Missing	-0.00	(0.00)

Table B.7 (Continued)

Variable	Employed	
Occupational Tenure	0.23	(0.01)
Occupational Tenure Squared/100	-1.09	(0.09)
Occupational Tenure Cubed/1000	0.14	(0.02)
Occupational Tenure*Disability	-0.02	(0.01)
Employer Tenure	0.35	(0.01)
Employer Tenure Squared/100	-0.21	(0.01)
Employer Tenure Cubed/100	-0.15	(0.00)
Employer Tenure*Disability	-0.00	(0.01)
Time Non-employed$_{t-1}$	-0.67	(0.01)
Local Unemployment Rate	-0.07	(0.01)
Unearned Income	-1.06	(0.03)

Notes: Standard deviations in parentheses.
Month and Year Dummies were also regressors but are not shown in the above table.
Estimates of permanent heterogeneity are available in Table B.10.

Table B.8: Coefficient Estimates from Disability Equation (Occupational Choice Model) (Jointly Estimated with Employment, Occupational Choice, Wages, Attrition, and Initial Variables Equations)

Variable	Moderately Disabled		Severely Disabled	
Age	0.19	(0.09)	-0.38	(0.10)
Age Squared/100	-0.30	(0.21)	1.21	(0.25)
Age Cubed/1000	0.02	(0.02)	-0.11	(0.01)
Non-White	-0.11	(0.05)	0.06	(0.06)
Unmarried	0.15	(0.04)	0.28	(0.06)
Number of Children	-0.05	(0.02)	-0.03	(0.02)
Education				
Less than High School	0.09	(0.05)	0.35	(0.07)
Some College	-0.05	(0.04)	-0.35	(0.07)
College	-0.41	(0.07)	-1.12	(0.12)
More than College	-0.53	(0.09)	-1.42	(0.18)
Region				
North East	-0.11	(0.05)	-0.11	(0.08)
Mid West	-0.10	(0.05)	-0.10	(0.07)
West	-0.03	(0.05)	-0.09	(0.07)
Non-metropolitan	0.07	(0.04)	0.02	(0.06)
Disabled$_{t-1}$	3.21	(0.09)	1.78	(0.14)
Severely Disabled$_{t-1}$	-0.80	(0.13)	2.05	(0.13)
For those who did not enter the survey disabled				
Time Disabled$_{t-1}$	1.05	(0.12)	1.37	(0.25)
Time Disabled Squared$_{t-1}$	-0.20	(0.05)	-0.26	(0.10)
Time Disabled Cubed$_{t-1}$/10	0.13	(0.05)	0.17	(0.09)
Time Disabled$_{t-1}$*Severe$_{t-1}$	-0.07	(0.03)	-0.08	(0.03)
Time Disabled Squared$_{t-1}$*Severe$_{t-1}$	0.02	(0.01)	0.02	(0.01)
Time Disabled Cubed$_{t-1}$*Severe$_{t-1}$/10	-0.01	(0.01)	-0.02	(0.01)
Enter the survey disabled	0.38	(0.11)	1.57	(0.14)
For those who entered the survey disabled				
Total Time Disabled$_{t-1}$	0.36	(0.04)	0.32	(0.04)
Total Time Disabled Squared$_{t-1}$/10	-0.19	(0.03)	-0.18	(0.02)
Total Time Disabled Cubed$_{t-1}$/100	0.03	(0.01)	0.03	(0.00)
Total Time Disabled$_{t-1}$*Severe$_{t-1}$	-0.00	(0.00)	-0.00	(0.00)
Total Time Disabled Missing$_{t-1}$	-0.50	(0.09)	-0.40	(0.11)

Table B.8 (Continued)

Variable	Moderately Disabled		Severely Disabled	
Health Insurance$_{t-1}$	-0.31	(0.05)	-0.41	(0.06)
Non-employed	-1.47	(0.13)	2.54	(0.28)
Hours Worked	-0.05	(0.01)	-0.00	(0.01)
Hours Worked Squared/100	0.03	(0.01)	-0.02	(0.01)
Small Employer (<25 Employees)	-0.03	(0.05)	-0.03	(0.16)
Small Employer*Disability$_{t-1}$	-0.06	(0.09)	-0.31	(0.19)
Medium Employer (25-99 Employees)	-0.13	(0.06)	-0.03	(0.18)
Medium Employer*Disability$_{t-1}$	0.02	(0.10)	-0.92	(0.27)
Occupational Characterisics				
Data	0.19	(0.09)	-0.07	(0.24)
Data*Disabled	-0.22	(0.15)	-0.04	(0.40)
People	-0.11	(0.08)	-0.01	(0.20)
People*Disabled	-0.02	(0.13)	0.56	(0.30)
Things	-0.09	(0.06)	-0.04	(0.13)
Things*Disabled	-0.06	(0.09)	0.20	(0.22)
Reasoning	-0.30	(0.13)	0.12	(0.33)
Reasoning*Disabled	0.47	(0.21)	-0.21	(0.53)
Math	-0.09	(0.11)	-0.04	(0.27)
Math*Disabled	0.29	(0.18)	0.14	(0.44)
Language	-0.09	(0.10)	0.12	(0.28)
Language*Disabled	0.08	(0.15)	0.43	(0.41)
SVP	0.01	(0.10)	-0.53	(0.25)
SVP*Disabled	-0.08	(0.17)	0.38	(0.41)
Strength	-0.08	(0.07)	0.33	(0.13)
Strength*Disabled	0.02	(0.10)	-0.08	(0.20)
Occupational Tenure	-0.00	(0.00)	0.01	(0.00)
Employer Tenure	-0.00	(0.00)	-0.17	(0.01)
Unearned Income	0.48	(0.04)	0.55	(0.05)

Notes: Standard deviations in parentheses.
Month and Year Dummies were also regressors but are not shown in the above table.
Estimates of permanent heterogeneity are available in Table B.10.

Table B.9: Coefficient Estimates from Wage Equation (Occupational Choice Model)
(Jointly Estimated with Employment, Occupational Choice,
Disability, Attrition, and Initial Variables Equations)

Variable	Wage	
Age	0.11	(0.01)
Age Squared/100	-0.24	(0.03)
Age Cubed/1000	0.02	(0.00)
Non-White	-0.07	(0.00)
Unmarried	-0.07	(0.00)
Number of Children	0.01	(0.00)
Education		
Less than High School	-0.13	(0.01)
Some College	0.07	(0.00)
College	0.25	(0.01)
More than College	0.36	(0.01)
Region		
North East	0.09	(0.00)
Mid West	0.03	(0.00)
West	0.12	(0.00)
Non-metropolitan	-0.12	(0.00)
Disabled	-0.21	(0.02)
Severely Disabled	0.02	(0.04)
For those who did not enter the survey disabled		
Time Disabled	-0.02	(0.03)
Time Disabled Squared	-0.00	(0.01)
Time Disabled Cubed	0.00	(0.01)
Severe Disability*Time Disabled	0.01	(0.01)
Severe Disability*Time Disabled Squared	-0.00	(0.00)
Severe Disability*Time Disabled Cubed	0.00	(0.00)
Enter the survey disabled	-0.02	(0.03)
For those who entered the survey disabled		
Total Time Disabled	-0.00	(0.01)
Total Time Disabled Squared/10	-0.00	(0.01)
Total Time Disabled Cubed/100	-0.00	(0.00)
Total Time Disabled*Severe	0.00	(0.00)
Total Time Disabled Missing	0.04	(0.02)

Table B.9 (Continued)

Variable	Wage	
Hours Worked	-0.05	(0.00)
Hours Worked Squared/100	0.11	(0.00)
Hours Worked Cubed/1000	-0.01	(0.00)
Small Employer (<25 Employees)	-0.12	(0.00)
Small Employer*Disability$_{t-1}$	0.00	(0.02)
Medium Employer (25-99 Employees)	-0.07	(0.00)
Medium Employer*Disability$_{t-1}$	-0.08	(0.02)
Employer Size Missing	-0.10	(0.04)
Occupational Characterisics		
Data	-0.00	(0.01)
Data*Disabled	0.06	(0.03)
People	0.01	(0.01)
People*Disabled	0.04	(0.03)
Things	0.06	(0.00)
Things*Disabled	0.04	(0.02)
Reasoning	0.01	(0.01)
Reasoning*Disabled	0.07	(0.04)
Math	0.04	(0.01)
Math*Disabled	0.07	(0.04)
Language	0.09	(0.01)
Language*Disabled	-0.01	(0.03)
SVP	0.08	(0.01)
SVP*Disabled	-0.10	(0.03)
Strength	-0.01	(0.01)
Strength*Disabled	0.08	(0.02)
Occupational Tenure	0.00	(0.00)
Occupational Tenure Squared/100	0.05	(0.01)
Occupational Tenure Cubed/1000	-0.01	(0.00)
Occupational Tenure*Disability	-0.02	(0.01)
Occupational Tenure Squared*Disability	0.10	(0.05)
Occupational Tenure Cubed*Disability	-0.01	(0.00)
Employer Tenure	0.01	(0.00)
Employer Tenure Squared/100	-0.01	(0.01)
Employer Tenure Cubed/100	-0.00	(0.00)
Employer Tenure*Disability	-0.02	(0.01)
Employer Tenure Squared*Disability	0.19	(0.04)
Employer Tenure Cubed*Disability	-0.04	(0.01)
Local Unemployment Rate	-0.01	(0.00)

Notes: Standard deviations in parentheses.
Month and Year Dummies were also regressors but are not shown in the above table.
Estimates of permanent heterogeneity are available in Table B.10.

Table B.10: Unobserved Heterogeneity Parameters (Occupational Choice Model)

Point of Support	Probability	Employment	Moderate Disability	Severe Disability	Wages
Permanent					
1	0.22	Normalized to 0			
2	0.19	-0.01	0.05	-0.05	-0.04
		(0.06)	(0.07)	(0.13)	(0.01)
3	0.28	0.15	0.07	-0.06	-0.05
		(0.05)	(0.07)	(0.12)	(0.01)
4	0.29	-0.32	-0.09	-0.11	0.02
		(0.06)	(0.07)	(0.14)	(0.01)

Notes: Standard deviations in parentheses.

Appendix C

Methods

C.1 Mixed Conditional Logit Estimation

Conditional logit models allow researchers to control for choice-specific variables. This is in contrast to traditional probit, logit, and multinomial logit models, in which only individual characteristics are valid controls. Accordingly, I use a mixed conditional logit equation that combines elements of a conditional logit and a multinomial logit model to estimate occupational choice, as characteristics of each occupation are likely important aspects of an individuals' decision.

Recall that in a multinomial logit equation, the probability that individual i selects option j is given by:

$$p_{ij} = \frac{e^{X_i \beta_j}}{1 + e^{X_i \beta_2} + e^{X_i \beta_3} + ... + e^{X_i \beta_J}}.$$

In a conditional logit, the probability that individual i selects option j is given by:

$$p_{ij} = \frac{e^{X_{ij} \beta}}{1 + e^{X_{i2} \beta} + e^{X_{i3} \beta} + ... + e^{X_{iJ} \beta}}.$$

For a given individual, in a conditional logit model the individual-specific variables will have the same value but the choice-specific variables may have different values. The individual-specific parameters are estimated in the same way as a multinomial logit equation, and in fact estimating a conditional logit equation with only individual-level variables provides identical estimates to those of a multinomial logit model. This produces $J - 1$ parameters for each individual choice variable, but only one parameter for each choice-specific variable.

Consider the estimation of occupational choice described in the paper, with 50 unique occupations. For simplicity, suppose we consider controls for the individuals' age (A_i), which varies across individuals, and strength required (S_j) in the occupation, which varies by occupation. The probability that individual i chooses occupation j is:

$$p_{ij} = \frac{e^{A_i\beta_j^0 + S_{ij}\beta^1}}{1 + e^{A_i\beta_2^0 + S_{i2}\beta^1} + e^{A_i\beta_3^0 + S_{i3}\beta^1} + ... + e^{A_i\beta_{50}^0 + S_{i50}\beta^1}}.$$

This would result in 49 coefficients estimated for age and one coefficient estimated for required strength. A positive coefficient for strength would indicate that individuals are less likely to select an occupation that requires strength, where as a positive coefficient would suggest that individuals are more likely to choose occupations that require strength.

The conditional logit model was developed by Daniel McFadden, and more details can be found in McFadden (1973).

C.2 Discrete Factor Random Effects Method

The Discrete Factor Random Effects method (DFRE) is a maximum likelihood random effects method used to control for unobserved (to the econometrician) characteristics that may be correlated across multiple equations. The DFRE method can be implemented either linearly or non-linearly, and in this research I use the non-linear version, as it is a more flexible approach.

To control for unobserved characteristics, error terms are decomposed in to three parts: a permanent component (μ), a time-varying component (ν_t), and a random component (ϵ_t). In a system of two equations, with error terms ξ_{1t} and ξ_{2t}, we have:

$$\begin{aligned}\xi_{1t} &= \mu_1 + \upsilon_{1t} + \epsilon_{1t} \\ \xi_{2t} &= \mu_2 + \upsilon_{2t} + \epsilon_{2t}.\end{aligned}$$

Not imposing a distribution on the error terms, the joint distribution of the error terms can be written generally as:

$$f(\xi_{1t}, \xi_{2t}|\mu, \epsilon_t) = f_1(\epsilon_{1t} - \mu_1 - \upsilon_{1t}) f_2(\epsilon_{2t} - \mu_2 - \upsilon_{2t}).$$

Integrating over the distribution of the permanent and time-varying components, the unconditional joint distribution is given by:

$$f(\xi_{1t}, \xi_{2t}) = \int \int f(\xi_{1t}, \xi_{2t}|\mu, \epsilon_t) dF(\mu) dF(\upsilon_t).$$

The cumulative distribution functions of μ and υ_t are estimated as discrete stepwise functions. The permanent components are allowed K steps, also known as mass points, and the time-varying components have L points of support. The probability of a particular permanent mass point is:

$$\rho_k = P(\mu_{1t} = \mu_{1tk}, \mu_{2t} = \mu_{2tk})$$

and the probability of a time-varying mass point is given by:

$$\psi_\ell = P(\upsilon_{1t} = \upsilon_{1t\ell}, \upsilon_{2t} = \upsilon_{2t\ell}).$$

These probabilities are estimated by the following equations:

$$\rho_k = \frac{exp(\gamma_k)}{1 + \sum_{k'=1}^{K-1} exp(\gamma_{k'})}$$

$$\psi_\ell = \frac{exp(\gamma_\ell)}{1 + \sum_{\ell'=1}^{L-1} exp(\gamma_{\ell'})}$$

where the DFRE model iterates to find the best values for $\gamma_{k'}$ and $\gamma_{\ell'}$ for the $K-1$ and $L-1$ mass points. The K^{th} and L^{th} mass points are not estimated, and are calculated as one minus the sum of the previous mass point probabilities, as the probabilities must both sum to one.

Using this stepwise approach, the unconditional joint distribution of the error terms can be approximated by:

$$f(\xi_{1t}, \xi_{2t}) = \sum_{k=1}^{K} \rho_k \sum_{\ell=1}^{L} \psi_\ell f(\xi_{1t}, \xi_{2t} | \mu = \mu_k, \upsilon_t = \upsilon_{t\ell}).$$

In estimating the parameters of a model using the Discrete Factor Random Effects method, an individual's contribution to the likelihood function is estimated in the same manner:

$$L_i(\theta, \rho, \psi) = \sum_{k=1}^{K} \rho_k \sum_{\ell=1}^{L} \psi_\ell L_i(\theta | \mu = \mu_k, \upsilon_t = \upsilon_{t\ell}).$$

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