

Exploring Occupational Characteristics and Their Impact on Employment Outcomes Among the Disabled

Denise Whalen*

University of North Carolina at Chapel Hill †

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Abstract

Although disabled workers may react to the onset of a disability by exiting the labor force, many disabled workers remain employed. Occupational change has been identified as a mechanism by which workers adapt to a disability and continue to work. In this paper I use information from the Dictionary of Occupational Titles in conjunction with the Survey of Income and Program Participation to identify the role that occupational characteristics play on occupational choice. Occupational characteristics considered include the use of data, math, reasoning, language skills, inanimate objects, strength, training, and the degree to which an occupation requires working with people. Estimation of a nonlinear random effects model accounting for permanent unobserved heterogeneity reveals that disabled individuals 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.

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†Department of Economics, 107 Gardner Hall CB #3305, UNC-Chapel Hill, NC 27599. E-mail: Denise.Whalen@unc.edu

1 Introduction

Historically, the majority of disability-related policy and economics research has focused on labor force participation among disabled individuals. While those with a disability are less likely to be employed than healthy individuals, almost 90 percent of moderately disabled men are employed. Employment transitions, such as changing occupations, have been identified as a mechanism by which workers adapt to a disability and continue to work. Specifically, depending on the severity, disabled workers are between 21 and 33 percent more likely to change occupations than non-disabled workers (Whalen, 2009). These transitions are found to reduce tenure, which reduces wages and employment rates of individuals with disabilities.

Although the effects of occupational transitions have been considered, economics research has yet to address how disabled individuals choose occupations, and how the characteristics of those choices effect outcomes including wages and disability status. Failing to account for occupational choice may produce biased estimates of the impact of occupational characteristics on a given outcome. The occupational characteristics considered include the requirement level of work with data, people, things (inanimate objects), reasoning, math, language, strength, and amount of specific vocational preparation (SVP) required. The pathway between these characteristics and work is straightforward: all else equal, a higher required skill level should lead to higher wages. These results, however, may differ by disability status if employers discriminate against disabled workers and offer them little to no wage increase for a given characteristics. Or, if a disabled worker is less capable of completing a task to a satisfactory level, we may also expect the increase in wages to be small or nonexistent. The relationship between occupational characteristics and disability status is less clear. Consider the impact of strength on disability status. Does working in a strength-intensive job lead to healthier and stronger individuals? Or, does working in a strength-intensive job increase the probability that a work injures himself carrying out a task?

The results indicate that individuals do select into occupations in a non-random manner. Disabled individuals choose occupations that have lower requirements of non-physical characteristics. These characteristics, in turn, effect disability status. For example, occupations that require working with people, things, language, and strength decrease the

probability an individual will be moderately disabled. Not surprisingly, seven of the eight characteristics have a positive impact on wages. These findings suggested that occupational choice accounts for part of the observed difference between disabled and non-disabled workers, and also influences disability rates.

2 Background

The notion that job characteristics influence employment decisions has been previously explored in the economics literature. An study by Chirikos and Nestel (1991) explores the effect of health on a variety of labor market outcomes of men aged 55 - 69. The authors find that an interaction between impairment and job type is not significant in determining labor force participation. Although this interaction is 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.

A 1996 Daly and Bound paper specifically looks at the role of job characteristics on labor market outcomes for those with a disability. Using the Health and Retirement Study (HRS), 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.

Occupation has also been explored as a contributor to health status. Cropper (1977) describes 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.

Developing a basic theoretical model and testing its implications, Kemna (1987) 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.

A study by Lakdawalla and Philipson (2007), explores the relationship between job characteristics and weight. The authors posit that declines in physically intense jobs, as measured by the Dictionary of Occupational Titles, have contributed to a sedentary lifestyle and more overweight individuals. The authors find that a worker who spends his working lifetime in an occupation requiring the highest degree of fitness will be almost 25 pounds lighter than a worker in the least physically intensive job. The authors acknowledge that selection is a concern in conducting such an analysis, and test for the presence of selection by weight. The tests reveal that selection is not present for men, but is a problem for women.

In this research, I estimate a series of equations that simultaneously control for selection into an occupation, as well as the effect of occupational characteristics on several outcomes. Estimates suggest that selection into an occupation based on disability status does occur, and thus controlling for selection is an advancement in the precision of such estimates. I additionally control for the presence of unobserved (to the econometrician) individual characteristics that may affect both disability status and employment outcomes. This approach produces sound estimates of the effect of occupational characteristics on disability status and wages.

3 Conceptual Framework

The goal of this research is to understand the interplay between occupational characteristics and disability. 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) and idiosyncratic (ϵ_t) characteristics:

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

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. Disability depends on many factors, including observable (X_t) and unobservable individual characteristics (μ), unearned income (Y_t), and current disability status (D_t):

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

Disability is also effected by a number of employment related outcomes. Occupational characteristics, captured by J_t , affect one's disability status, as job tasks may have a direct effect on health. 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. The length of time a person has been performing job tasks or in a given work environment, as captured by occupational (OT_t) and employer tenure (ET_t), also influence disability status.

4 Empirical Model

In this section, I focus on the empirical specifications used to determine how individuals choose occupations. Consider the choice among R occupations:

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

The optimal outcome chosen by an individual 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. 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 multinomial logit model. To incorporate both sets of variables, the probability of an unobserved occupational outcome is estimated as a mixed conditional logit model.

Conditional logit models allow researchers to control for choice-specific variables.¹ 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 individual's decision.

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

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

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

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

¹The conditional logit model was developed by Daniel McFadden, and more details can be found in McFadden (1973).

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:

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

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.

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.

5 Data

In this research, I use data from the 1996 panel of the Survey of Income and Program Participation (SIPP). 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 specific focus of the SIPP is not directly on disability or employment, large amounts of data on these topics have been collected.

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 thousands of jobs. 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)). For the purpose of this study, 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 SIPP defines occupations using 1990 Census codes. There are just over 500 Census codes, but over 12,000 DOT codes. Using a crosswalk provided by the National Crosswalk Center, I assign DOT codes to each of the SIPP codes. However, each SIPP occupation may have multiple DOT occupations codes. As SIPP occupations were assigned several DOT definitions, the median of the characteristics for each DOT code was used. If the median occurred between two numbers, the higher (more difficult) value was assigned 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.² 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 1. Examples of occupations by characteristics levels are contained in Table 2. Considering data again, a farm worker is an example of an occupation that has the lowest requirements of data use, and lobbyists lie at the other end of the spectrum. To ease the computational burden in the analysis, I discretize the job characteristics to represent a low or high level of that characteristic.³ The cut-off values were assigned so that occupations with the lowest 50% of job characteristics had values assigned to 0, and the other half were assigned to 1. The discrete assignments can be seen in Table 3.

Table 1: 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 1. 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 requirements. In addition to estimating occupational choice, this paper will analyze the effects that these occupational characteristics have on disability status. For

²DOT rankings have been shifted so that 0 represents a low requirement level, and higher values indicate increased requirements in that category.

³Discretizing characteristics produces 50 unique occupations selected by survey participants. If occupational characteristics were not discretized, there would be over 1,000 times as many occupations.

Table 2: 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 3: Discretizing Job Characteristics

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

Figure 1: Distribution of Job Characteristics by Disability Status

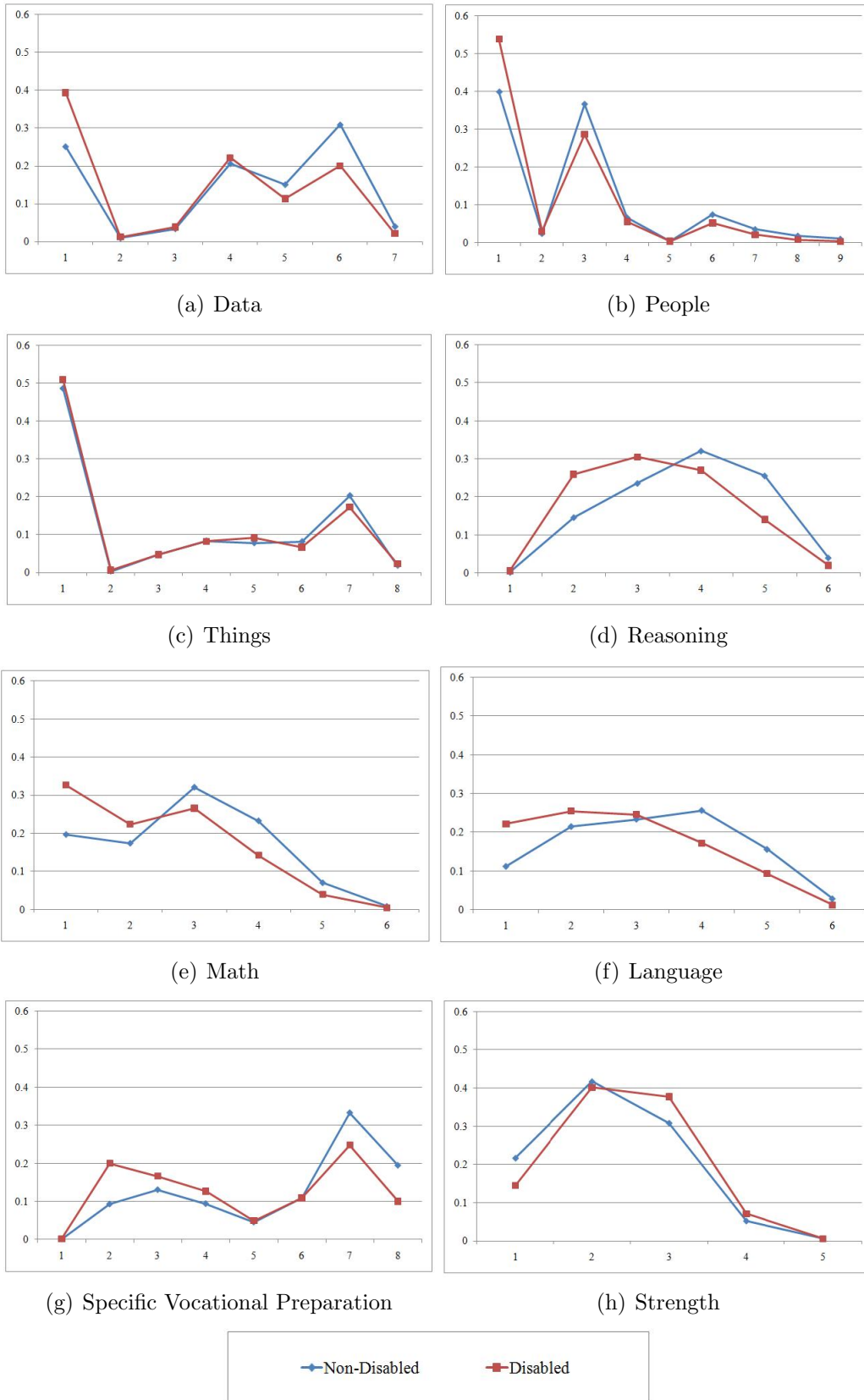


Table 4: Characteristics by Disability Status

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

example, perhaps the choice of disabled individuals to continue in occupations with high strength requirements contribute to continued disability. The differences also exist across each level of disability, as can be seen in Table 4. With the exception of strength, nearly all characteristics levels are highes for the non-disabled, followed by the moderately disabled, and lowest for severely disabled workers.

6 Results

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. 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 5, 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

Table 5: 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. 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. 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 of opportunities available to this group. The notion that there are barriers

Table 6: 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 heterogeneity

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

to certain types of employment is an important piece of the employment puzzle regarding disabled individuals.

Table 6 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 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 7 contains the results for the marginal effects of the characteristics on disability status. The majority of the

Table 7: Marginal Effects of Occupational Characteristics on Disability

Variable	Moderate Disability		Severe Disability	
Data	0.27 (0.22)		-0.11 (0.27)	
People	-0.41 (0.15)	***	0.27 (0.11)	***
Things	-0.30 (0.14)	**	0.11 (0.11)	
Reasoning	-0.32 (0.27)		-0.02 (0.18)	
Math	0.11 (0.18)		-0.04 (0.19)	
Language	-0.30 (0.18)	**	0.32 (0.18)	**
SVP	-0.03 (0.21)		-0.24 (0.28)	
Strength	-0.27 (0.13)	***	0.28 (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 8 describes the marginal effects of occupational characteristics on log wages

Table 8: 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

for disabled workers. Working with data, people, things, reasoning, math, language, and strength 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.

Occupational Selection

The results presented suggest that occupational selection by disability does occur. To assess the magnitude of bias that occurs if one fails to control for selection, I have estimated the same framework as described above, without controlling for selection. Table 9 compares the results of estimates from the wage equation using the incomplete framework to the correct results presented in the previous section. 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.

Table 9: Marginal Effects of Occupational Characteristics on Wages, By Model

Variable	Log Wages			
	NOT Controlling for Selection		Occupational Choice Model	
Data	0.068 (0.024)	***	0.055 (0.029)	**
People	0.121 (0.027)	***	0.054 (0.029)	**
Things	0.065 (0.015)	***	0.097 (0.020)	***
Reasoning	0.085 (0.040)	**	0.078 (0.044)	**
Math	0.035 (0.036)		0.107 (0.029)	***
Language	0.082 (0.022)	***	0.086 (0.038)	**
SVP	0.008 (0.024)		-0.019 (0.029)	
Strength	0.079 (0.025)	**	0.071 (0.028)	***

Note: Bootstrapped standard deviations are in parentheses.

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

7 Conclusion

This study extends the limited research that has been conducted regarding disabled individuals who remain employed. While disabled individuals may exit the labor force upon the onset of disability, many continue to work for many years with a work limitation. Understanding the choices made by these disabled workers may be a key to successful disability policy.

One goal has been to assess the role of disability on occupational choice. The results indicate that employed disabled individual select occupations that have lower requirements in seven of the eight occupational characteristics considered, compared to employed non-disabled individuals. As the source of the disability is not identified in the model, it is difficult to conjecture why these choices are made, particularly if a people with a physical

limitation choose occupations with low levels of occupational characteristics that are non-physical. Understanding why these choices are made is an important research question.

Controlling for occupational choice allows us to answer another key question: How do occupational characteristics affect disability status and wages? Estimates suggest that occupational characteristics have different effects depending on the severity level. Working with people, language, and strength, for example, all decrease the probability an individual is moderately disabled but increase the probability an individual is severely disabled. Identifying these beneficial characteristics and promoting them in the work place may aid in developing a workforce with a lower incidence of disability. Results also show that occupational characteristics are either insignificant or beneficial to wages. Overall these findings suggest that investing in development of certain skills may produce a healthier and wealthier workforce.

A Appendix

Table A.1: Coefficient Estimates from Employment Equation

(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 A.1 (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 A.5.

Table A.2: Conditional Coefficient Estimates from Occupational Choice Equation

(Jointly Estimated with Employment, Wages,
Disability, Attrition, and Initial Variables Equations)

Variable	Employed	
Occupational Characteristics		
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 A.5.

Table A.3: Coefficient Estimates from Disability Equation
(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 A.3 (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 Characteristics				
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 A.5.

Table A.4: Coefficient Estimates from Wage Equation
(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 A.4 (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 Characteristics		
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 A.5.

Table A.5: Unobserved Heterogeneity Parameters

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

Notes: Standard deviations in parentheses.

B 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:

$$\xi_{1t} = \mu_1 + \nu_{1t} + \epsilon_{1t}$$

$$\xi_{2t} = \mu_2 + \nu_{2t} + \epsilon_{2t}.$$

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

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

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

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

The cumulative distribution functions of μ and v_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:

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

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:

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

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:

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

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