Examining the Effect of Technology on Disabled People's Wages

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March 15, 2017

Abstract

This article presents for the first time a study of the extent of effectiveness of computer use on earning power of disabled people. Disabled people face struggles and discrimination in the workplace and this causes a wage gap to arise between them and their non-disabled counterparts. In order to examine said wage gap, I exploit the Bureau of Labor Statistic Current Population Survey and its special supplement on Internet and computer use bi-yearly from 2011 to 2015. This research paper focuses on the wage gap produced by computer use and disabilities in the work place as well as the level of affect computer use has on the income or earning power of disabled workers. The nature of the data in this study allows for a broader perspective on this subject, which is a new angle than what has been studied in previous research. Earning regressions were used to estimate the effect of computer use on disabled wages. The significant diversity across America and its disabled population are captured and incorporated by a number of different variables in the model. The findings in this paper show that some disabled workers who use computers earn more than disabled workers who don't use computers. However, the lack of robust findings supports the belief that although results were found to be significant there are no strong economic or rational arguments to explain this correlation.

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I Introduction

Disabled people face discrimination in the workplace very often. Disabled discrimination manifests itself in many different ways. One of the most detrimental ways is wage discrimination. This wage discrimination has caused another wage gab between disabled workers and their non-disabled counterparts. Discrimination is often caused by preconceived notions about how disabled people work, like how they work less productively, making worse quality and less quality (Basas 2013). The decreased earning power disabled people experience discourages these people from working and trying to find new work. It also hurts the fiscal well being of the disabled persons family (Jolly 2013). This financial dependence severely hurts the family income. There have been some suggested solutions to these problems like information sessions and accommodative technology amongst other things.

The earning power and income of disabled people have been researched in various ways across the globe. These effects have been examined by creating models in previous literature. In Spain the wage gap was examined to measure the severity of income loss of disabled people (Cervini-Pla, Silva, and Castello 2015). This study focused on the size of the wage gap, and to what extent did disabled workers earn less on a monthly basis. Across Europe, the estimated effects of income and wage disparity on welfare were examined (Anton, Brana, and Munoz de Bustillo 2016). Their focus was on the cost that disability had on wages and how this differed throughout Europe. The majority of the previous literature and research included personal characteristics as a binary or dummy variable. A study on disparity in the Philippines focuses on the effect of education and gender on disabled peoples' income. Other research examines the effect that disability has on income mobility, as well as the effect that their location has on the distribution of income (Jolly 2013).

Most of these studies use independent variables that directly represent disability, or severity of disability, using simple binary variables. Other studies use independent variables that indirectly represent disability. The most common indirect representation of disability, used as both independent and dependent variables, is income disparity. In the existing literature, several models of disabled earning have been examined. The effect that being disabled has on the wage gap and income mobility has been researched and, on the other hand, the effect that income and wage gap have on welfare has also been examined. Also, a few studies researched the factors that could possibly account for the disabled income disparity. One aspect of the literature that is missing is the research of the magnitude of the effect of accommodative factors on the disabled income disparity.

Technology is an important tool that can help disabled people by allowing people to regain abilities that they lost (Basas 2013). Accommodations like electric wheel chairs let people travel with ease, but technology can be used for more than just tools, such as prosthetics. The computer is an incredible piece of technology and a tool that aids disabled people. The right use of accommodative technology will enable disabled employees to strive in their work place. The magnitude of the effect of computer use on disabled income will be examined in this research study. The key variables used in this study are hourly wage, computer use and disability. This will help indicate whether or not computer use is a good solution for decreased disabled wages and the disabled wage gap. Also, the results will allow us to decide if investing in computer use is worthwhile attempt to combat the disabled wage gap.

The progression of this report is as follows. Section Two provides a review of the existing literature regarding the disabled wage gap. Section Three outlines the data and variables as well as the econometric model used in this research. Section Four describes the methodology and design of the models used. Section Five discusses results of the regressions analysis, and conclusions are provided in Section Six.

II Background and Related Work

In the mid 90's a exemplary model was constructed to examine the factors that affected disability. Stone and Colella (1996) created a model in hopes it would be used and altered by other researchers in their model. In their model the working and non-working disabled were included. However, the factors that could offset the challenges disabled people face were not included in their study.

Basas (2013) examined the correlation between the contributing factors and disabled peoples' decreased income. Some of these contributing factors examined are discrimination, social norms and expectations, and lack of technological accommodation. Basas (2013) further analyzed the factors, using data from a private source, to see which one was the most impactful on the disabled employee. Technology is a major factor in the aid of disabled people. Technological accommodation, specifically computer use, was found to help remedy the issues disabled people faced in the workplace (Basas 2013). Increasing technological accommodations for disabled increases their productivity, effectiveness and morale.

Discrimination is often caused by preconceived notions about how disabled people work, like how they work less productively, making worse quality and less quality (Basas 2013). This wage discrimination has caused another wage gab between disabled workers and their non-disabled counterparts. The social stigma around disabled workers causes some employers to incur extra costs to avoid contact with these type of minority groups (Basas 2013) and (Rodgers, Marjorie, and William 2006). Rodgers, Marjorie, and William (2006) further described the economic theories of discrimination in action against disabled people. The three theories brought to attention were prejudice, information problems, and exploitation. Prejudice is the employers willingness to pay more to not have to hire or deal with minority workers, specifically the disabled. The prejudice theory discussed by Rodgers, Marjorie, and William (2006) predicts that employers who are prejudiced will not hire disabled workers unless they are willing to take on lower wages than the non-disabled workers, who do not face any prejudice. Information problems are an economic theory that is based off of the prejudice theory. This theory states that discrimination stems from asymmetrical information in the labor force or statistical discrimination. Statistical discrimination models assume that it is harder to measure the productivity of a disabled worker, compared to a non-disabled worker, because of the differing characteristics of the disabled minority group. The exploitation theory suggests that employers exploit minority workers to increase their profits. When this theory is applied to the disabled minority group it is effectively an exploitation premium, which is the minority groups inability to demand equal treatment and pay in the market. This exploitation premium also supports the fact that disabled people have lowered job and income mobility and also have a harder time changing occupations.

Tennant (2012) studied veterans who are disabled and their earning capabilities. She conducted research on wage gap on a specific sample of only the recent veterans. Often, veterans are faced with sever discrimination after returning from war. In addition, when veterans return with a disability it further contributes to the discrimination that they face. It is difficult for veterans to assimilate back into culture and even harder for them to get hired again. Often times these people end up homeless or have to live in veteran's hospitals because they fail to assimilate back into society. She found that disabled veterans made significantly less compared to non-disabled veterans. The decreased earning power disabled people experience discourages these people from working and trying to find new work. It also hurts the fiscal well being of the disabled persons family (Jolly 2013). This financial dependence severely hurts the family income. Disabled people often have a heavy fiscal reliance on their immediate family members, which is often caused by the disabled person's inability to take care of himself or herself. Sometimes, the financial burden put on these families causes them to fall below the poverty line.

An important correlating factor researched relating to both technology and disabled income is poverty rate. Jolly (2013) analyzes the socio economic struggles of disabled people in the work place. Jolly (2013) examines work limiting disabilities affect on earnings and income mobility of those individuals. The factors he used to analyze disabled earnings were spouse's earnings, duration of disability and severity of disability. Like other minorities when disabled people are at a disadvantage it is harder for them to over come said disadvantage because of the discrimination and the preconceived social notions about disabled people. Disabled income and poverty rate have a very high correlation.Jolly (2013) produced results that supported that work-limiting disabilities effect wages and also how these disabled workers have less upward mobility in the workplace. Cervini-Pla, Silva, and Castello (2015) studied the earning gap between disabled workers and their non-disabled counterparts. They created a model to estimate the effects of the factors on disabled income. Like Jolly (2013), Cervini-Pla, Silva, and Castello (2015) obtained data from government run databases. Their research looked at the wage gap by examining the correlation of disabled income, age, sex and duration of disability with non-disabled income. They found that disabilities entail reduced earnings. The key dependent variable used in the analysis of their data is the wages of the non-disabled individuals. This is the only research that has considered non-disabled income as their dependent variable. Cervini-Pla, Silva, and Castello (2015) found that yes, in fact, the earnings of disabled were significantly less per month. This income disparity is very apparent in the majority of the research on disabled earnings because it exemplifies reduced disabled earnings well. In one study, the income disparity of the disabled was examined based on the education and sex of the people (Albert et al. 2015). The more education the disabled worker had achieved the more they earned, which was expected. Also their results suggested that disabled women have twice the disadvantage in earning power compared to men.

Labor market discrimination occurs across genders but is much stronger for women. Because of this, in regression results disabled men often show no significance or low significance to disabled earnings compared to women (Albert et al. 2015). In research done by Marjorie and William (1994) only disabled males were focused on so to exemplify the significant correlation between reduced earning. In this research disability is broken down to represent the intensity of disability. They distinguish between people who are impaired, handicapped, and disabled [1]. Analysis of reduced disabled earnings has been measured in various different ways through dependent variables. A common dependent variable used in this research is income. One common dependent variable is log hourly wage as used in Marjorie and William (1994), William and Lambrinos (1985), Cervini-Pla, Silva, and Castello (2015) and Albert et al. (2015). This allows for direct analysis of wages of disabled and non-disabled workers and the wage gap between them. Marjorie and William (1994) found that the disabled wage gap increased from 1972 to 1984. This wage gap increase is correlated with an increase in cost of disability in the market (Anton, Brana, and Munoz de Bustillo 2016). One way the cost of disability has been studied is by examining the earning capability of people. If disabled workers do in fact make less money than their non-disabled counter parts this should be apparent in the lower earning capability of disabled people. Reduced disabled earnings have been a topic of interest across the globe. Anton, Brana, and Munoz de Bustillo (2016) studied reduced disabled earnings by examining the change in earning capabilities of disabled compared to that of non-disabled across Europe. They found that there is a significant difference in the cost of disabilities across the european countries they examined. Income loss due to disability was also researched in the Philippines by Albert et al. (2015). They found that there is a significant income disparity between disabled workers and non-disabled counterparts. Also their results showed that disabled men have a significant disadvantage compared to non-disabled men and further

1. These three definitions of disability were retrieved from the World Health Organization (WHO) and are outlined by Marjorie and William (1994)

more, women are at an even further disadvantage compared to disabled men and non-disabled women. Disabled people were found to have a high correlation with lower education. One aspect of disability that the majority of the research leaves out is the onset of disability, as many disabled people were not born with their disability. Gilleskie and Hoffman (2014) use health capital and human capital as tools to explain wage disparities due to disabilities and specifically the onset of a disability. Their results showed that an onset of disability causes an immediate negative impact on earning power. Furthermore they found that disabled male workers are twenty nine percent more likely to change job or occupation than non-disabled males.

In a couple of studies the initial results showed no significant correlation or only marginally significant correlation between disability and decreased wages. This is due to selection bias in the sample of the data being used for the regression. Both Marjorie and William (1994) and William and Lambrinos (1985) had to deal with this selection bias issue, which is described in further depth below. Once the models were adjusted to account for the selection bias significant results were found. Specifically William and Lambrinos (1985) found that handicapped men earn about seventeen percent less than non-handicapped men. However, the classifications used by William and Lambrinos (1985) for disabled differ from those used by Marjorie and William (1994) a great deal.

There are a few methodological nuances and problems that arise when researching disabled people in the work place. Stone and Colella (1996) brought to attention the challenges of strictly defining disabilities and fraudulent portrayal of being disabled. The way to conduct accurate research is dependent on the accuracy of the data pool. When researching disabled workers the sample selection bias occurs and can skew results if not dealt with properly (Rodgers, Marjorie, and William 2006). Both Marjorie and William (1994) and William and Lambrinos (1985) deal with the selectivity bias issue in their research by using a selection model, specifically the Heckman Model. When averaging hourly wage of disabled without use of a selection model the result is severely reduced.

All workers who use computers make eighteen percent more than those who do not (Autor, Krueger, and Katz 1998). DiNardo and Pischke (1997) examine the same phenomena but with the use of pencils in the workplace. They found that people who use pencils in the workplace also made fourteen percent more than their non-pencil using co-workers. Since computer use and pencil use in the workplace represent the same type of factor used to increase wage DiNardo and Pischke (1997) argue pencil use in the workplace may not be different than computer use in the workplace. This wage gap between pencil users and non-users is not evidence to argue skill bias based on technological change. Pencil use skill is not a skill biased technological change because it does not require very much skill to use. Also with a change in technology the skill set needed to use a pencil does not change and no aspects about pencil use need to be relearned. On the other hand, computer use can be considered a skill biased technological change because it requires skill to be able to use a computer well. Computer use skill also allows for other useful skills to be learned and occasionally requires relearning some of the computer use skill aspects due to change in technology.

Basas (2013) researched use of different technological accommodation, using data from a private source, to examine which ones were the most impactful on the disabled employee. He examined the issues that disabled people face in the work place and the technological accommodations that can be made to help. Basas (2013) found that the majority of the issues that disabled people face in the work place could be remedied by technological accommodations. Increasing technological accommodations for disabled increases their productivity, effectiveness and morale. Some of the technological accommodations he proposed are: providing qualified readers or interpreters, schedule restructuring, job restructuring, reallocation and purchasing and modifying equipment. Recently developers of upcoming technology have turned their focus to accessibility and usability for disabled people (Thier 1983). The use of technology, more specifically computer use, may help disabled people earn more money in their career. Different people and companies have developed tools to help amputees and people with paralysis with simple, but useful, things like computer use. Computer use can be very beneficial to specific groups of disabled workers, as studied by Kruse, Krueger, and Drastal (1996), which focused on spinal cord injury patients. The research they conducted focused on the ability of the spinal cord patients to use, adapt and take advantage of the technology presented to them. They found that it was often hard for the patients to adapt to the technology but once they did it was very helpful to them. They also brought to attention how the patients lowered ability to get a job, retain the job, and earn as much as their non-disabled counterpart. They found that almost half of the patients who were comfortable with the technology were better equipped and able to secure and retain a job. But overall, they concluded that disabled people have lower income and job mobility and earn less than non-disabled people.

Most of the previous literature on this topic examines the correlation between the factors that affect decreased income and wages of disabled workers as Cervini-Pla, Silva, and Castello (2015) and Jolly (2013) do. These aspects have ranged from types of discrimination to comparison to non-disabled wages. One question that has not been researched is how effective are the factors that counter decreased disabled income, specifically the effectiveness of computer use. Previously only the downward correlating aspects of disabled peoples income have been examined. My research aims to analyze the increasing correlation between technology use and disabled workers income.

III Data and Variables

The kind of data needed for this research is pooled cross-sectional data, which was obtained from surveys. The data needs to include information on income or wages, computer use, personal characteristics and information, and disability. This type of data is required as to control for other factors that may affect wages and because the trends over time need to be accounted for. The key variables needed are an hourly wage dependent variable and disabled, computer use, and the combination of the two for independent variables. These variables are used to examine effects of disabled computer use on their earning power. All three of these key independent variables have binary values.

There are multiple binary or dummy variables that may explain the disabled wage gap. These variables represent the personal characteristics of people, including everything from race to occupation. Variables like high school or black have high correlation with with hourly wage and appear to explain the disabled wage gap, but also explain other disparities in income not being researched. For example, less educated people earn significantly less leading to a high correlation with low hourly wage. Disabled and some form of income are naturally independent variables used in most research. Other controlling factors are accounted for by dummy variables like yearly fixed effects and an error term. These variables account for the change in hourly wage that can not be explained by the other variables.

The data used in this research project was retrieved from the Current Population Survey (CPS) by the Bureau of Labor Statistics. This data is derived from surveys given to every household across the United States. The dependent variable in my research will be the wages or income of the disabled and non-disabled people. In the data used for my research project, the independent variables represent technology use in the workplace and the other potentially related factors that might affect disabled income. The data on computer use is located in a CPS Supplemental survey. The Computer and Internet Use Supplement was first administered in July 2011 and was continued in July 2013 and July 2015. The data was retrieved from the supplement database and manipulated and altered so it can be analyzed in the desired way for the required research.

Log Hourly Wage is the only dependent variable, which is numerical and that represents the logarithm of each person's hourly wage. Since the last year of the data used is 2015, the hourly wage is in terms of 2015 dollars. The log of the hourly wage is used because it is a large value and the log makes it a comparable scale of rest of the variables. This variable is also used in other research as the dependent variable (Marjorie and William 1994) and (William and Lambrinos 1985). The logarithmic-linear form model used in this research allows us to interpret the results in terms of percent also, which makes analysis of the results easier. This variable is used as the dependent variable because we want to analyze the impact of the various factors on income or wage. *Log Hourly Wage* is important because it can represent the wages of the disabled and non-disabled who both use and do not use computers at work. This will allow a full comparison of the wage gap caused by disabilities and computer use.

A crucial independent variable in the raw data is *CompUse*, which is a binary variable that indicates whether or not the worker uses computers in the workplace. Technology accommodation in the workplace has been shown to alleviate the income disparity between disabled workers and their non-disabled counterparts Basas (2013) and Cervini-Pla, Silva, and Castello (2015). When the worker uses computers in the work place CompUse equals one and otherwise it equals zero. There are more extensive variables that will be used to describe the level of computer use by any given person. These variables are also binary and so the person either does that computer action or does not.

There are six specific disabled variables that describe the extent of disability that person possesses. These

Dependent Variable	Description
Log Hourly Wage	Log of the hourly wage of people

Independent Variable	Description
compuse	1 if the person uses computers; 0 otherwise
Disabled	1 if the person is disabled; 0 otherwise
Disabled*Computer Use	1 if person is disabled and uses computers; 0 otherwise
female	1 if the person is female; 0 otherwise
age	The of the person in years
age^2	The age of the person squared
Metro	1 if the person lives in a metro area; 0 otherwise
Married	1 if the person is married; 0 otherwise
Dummy Variables	Dummy Description
Occupation	Occupation of person categorized into 11 different categories, 10 different dummy variables
State	State where person lives each state is represented by a different dummy variable
Industry	the industry the person works in categorized into 14 different categories, 13 different dummy v
Race	Race Description: Reference race category is white
Black	1 if the person is black; 0 otherwise
Hisp	1 if the person is hispanic; 0 otherwise
Other	1 if the person is white; 0 otherwise
Education	Education Description: Reference education is less than high school
hisch	1 if the person is a college grad; 0 otherwise
somcol	1 if the person has completed some college; 0 otherwise
morecol	1 if the person is a high school grad; 0 otherwise

Table 1: Description of Variables Table

variables are binary variables that represent if the worker is deaf, blind, mental problems, physical problems, motor skills problems and social issues. These variables are represented by *Deaf*, *Blind*, *Memory*, *Physical*, *Selfcare* and *Errands* respectively. Another important independent variable is *Disabled*, which is a binary variable that indicates whether or not the worker is disabled. When a worker identifies with any of the six specific disabled variables, the *Disabled* variable equals one. This is an important variable in the model because it represents the population of workers who are disabled. This will be used too compare the income of disabled who use computers and disabled who do not.

Deaf and *Blind* are dummy variables that simply represent if the worker identifies as deaf or blind. The variable *Memory* represents if the person has serious difficulty concentrating, remembering or making decisions because of a physical, mental or emotional condition. *Physical* represents if the person has serious difficulty walking or climbing stairs. The variable *Selfcare* represents if the person has difficulty dressing or bathing. Lastly *Errands* represents if the person has serious difficulty running errands such as visiting a doctor's office or shopping because of a physical, mental or emotional condition.

Disabled is also an important variable because it represents the disabled people who use computers in the work place. This dummy variable is arguably the most important variable because it captures the sample of workers that use computers who are also disabled. When the person is disabled and uses computers then *Disabled* equals one. This variable uses the base disability variable and base level of computer use to combine the two since the other disability variables get too specific. Using the base levels of the variables allows for every disabled person that participates in any type of computer use.

This *CompUse* variable is separately combined with the general disabled variable and the specific disability variables to create *Disabled* * *Computer Use* interaction terms. In total seven disabled interaction terms were created, one for each of the specific disability terms and one for the general disabled variable. These interaction terms are the key independent variables in the models used in this research.

There are seven other descriptive independent variable categories used in the model. These variables represent gender, age, occupation, job, race, location, and education level. Of each of these dummy variable categories one variable is left out because that part is statistically represented by the part of the data that is not there. For example as a result only *Female* is used out of *Male* and *Female*. These variables are personal descriptive statistics that explain change in wage and are commonly used in this type of model (Cervini-Pla, Silva, and Castello 2015) and (Jolly 2013). Past research that has been done on the disabled wage gap includes these control or descriptive variable categories. These variables are important in the model because they account for the extraneous affects on wages.

Age is represented as both itself as well as Age^2 to put it in multiple terms. The Age^2 variable will estimate how age relates to these other variables, dependent and independent, capturing a non-linear relationship.

Analyzing this correlation data on a non-linear scale might give us insight on why the variable interacts the way it does. Also, this Age^2 variable represents an accelerated depiction of age, which allows us to analyze how getting very old effects wage.

Metro represents if the person lives in a metropolitan area. This is important because depending on what kind of environment you live in different earnings are expected. In general people who live in metropolitan areas earn less than people who do not live in metropolitan areas. This is driven by the influx in minorities that live in these areas. It is necessary to include this variable because of it's possible affect on hourly wage and needs to be accounted for. The *Married* variable represents if the person is married. This is important to add because when a worker is married they generally earn slightly more (Marjorie and William 1994).

State represents where the person lives and is separated into dummy variables for each state. Every state and province of America has its own dummy variable but one will be left out leaving a total of fifty dummy variables [2]. If the person lives in that state then that location variable equals one and the rest of the location variables equal zero. *Year* is another group of dummy variables that is included. This variable represents what year the data is being reported. This allows us to consider the changes in hourly wage due to year specific effects.

Race is broken down into four major categories: *White*, *Black*, *Hispanic* and *Other*. If the worker is, or racially identifies, as any of the three groups then that variable will equal one and the other race dummy variables will be equal to zero. This variable should show us the wage gap and general socio-economic struggle of minorities in the market. The *White* variable represents if the worker is or racially identifies as white. The reference group for race is white people. It is important to include race because some races make significantly less than other races and also face larger amounts of discrimination, so this needs to be accounted

2. The 51 states included in this variable include Alaska, Hawaii, and the District of Colombia. The reference state used is Wyoming.

for in the model.

The Education dummy variables represent the extent of education the person has completed. The highest level of education variable is *More College*, which assumes they fully completed four years or more of college. The *Some College* variable represents when the person has completed less than four years of college education. Lastly, the *High School* variable represents when the person has only completed up to a high school level of education. The reference group for education is the people who have not completed a full high school education. Education level is an important factor that is known to significantly effect wages. Workers with high school educations generally earn substantially less than workers with college or even some college education.// *Occupation* and *Industry* do in fact seem similar but occupation is what job the person does in their company and industry is what that company does or makes. *Occupation* is a variable that represents what occupation the person works in. *Industry* represents the industry their company is classified under. These variables are broken down into industry and occupation categories, which range from financial occupations to armed forces. The *Industry* has eleven different categories that are made into ten different dummy variables. The *Occupation* has fourteen different categories that are made into thirteen different dummy variables.

IV Economic Model

This section describes the econometric model used in this analysis. In addition to discussing each of the dependent and independent variables, this section outlines the statistical methodology used in this study.

IV.I Econometric Model

Previously only the negative aspects of disabled people's income have been examined. These aspects have ranged from types of discrimination to comparison to non-disabled wages. My research aims to analyze the positive relationship between computer use and disabled workers income. A. Econometric Model to Estimate the Correlation between income and use of technology by disabled to examine the effect of use of technology on the income of disabled workers; this study uses the following econometric model:

$$\begin{aligned}\text{LogHourlyWage} = \beta_0 &+ \beta_1\text{Computer Use} + \beta_2\text{Disabled}\\ &+ \beta_3\text{Disabled * Computer Use} + \beta_4\text{Age} + \beta_5\text{Age}^2\\ &+ \beta_6\text{Education} + \beta_7\text{Race} + \beta_8\text{Gender}\\ &+ \beta_9\text{Married} + \beta_{10}\text{Metro}\\ &+ \beta_{11}\text{State dummies} + \beta_{12}\text{Year dummies} + \epsilon\end{aligned}$$

where ϵ is a stochastic disturbance term.

The *Disabled * Computer Use* interaction term is the key independent variable in this model, which is a variable that represents if a worker is disabled and uses computers in the work place. Equation 1 of the appendix presents the secondary model used to analyze the effect of computer use by specific disability variables on hourly wages. Rather than having the one general disabled and computer use interaction term, (in the appendix) Equation 1 model specific disability and computer use interaction terms are used. In both the equation presented and appendix equation one these interaction terms are expected to have a positive correlation. Computer use has been known to help mitigate the challenges disabled workers face that causes a decrease in productivity (Basas 2013). Therefore, these disabled workers who use computers are expected to earn more than disabled workers who do not use computers.

Several control variables, which are described in the Data and Variables section, are used to measure outside effects on the change in hourly wage. In earning regression models controls are essential to getting accurate results. If these controls are not included important contributing factors to the change in the dependent variable are left out, which leads to skewed results. The race variables are expected to have negative signs because the control groups, white people, on average are expected to earn more than the other three races included in the model. As education increases so does the ability to earn more money. So the education variables are expected to be positive because the control group is the lowest level of education.

Controls account for the general characteristics of people that may cause a change in hourly wage; however, the external environmental factors are measured in a different way. Depending on the state the person lives in they will earn more or less money due to the tax regulations and job availabilities in that state. The State dummy variables represent the state specific environmental factors that may affect hourly wage, which is called state fixed effects. The Year dummy variables act similarly, as they represent the year specific environmental factors or events that may affect hourly wage, which is called yearly fixed effects. An example of fixed effects, specifically yearly fixed effects, is in 2008 because of the recession the average wage of workers decreased due to the recession's financial impact on the market.

In the initial regression model occupation fixed effects and industry fixed effects were also included. These variables represented what job the person is doing and in what industry they are doing it. In addition, these fixed effects also represent the change in hourly wage due to events specific to industries or occupations. *Union* was also a variable used in the initial regression model, which represented if the person was part of or participated in a workers union. These occupation and industry fixed effects and *Union* variables were not included in the final regression models because of sample selection bias, which will be touched upon in the next section.

IV.II Methods and Design

This paper estimates the econometric model using ordinary least squares (OLS), Heckman-probit, and Heckman-OLS Regressions. In all three of the different regressions methods there are at least two models used and the difference between the two models is the use of general disability and specific disability variables. Initially OLS regressions were ran, Equations Two and Three in the appendix, and the results were not consistent with the assumption that disabled workers earn less than non-non-disableddisabled workers. The effect of the disability variable appeared to not be significant, which was on the contrary to the results of previous literature (Marjorie and William 1994) , (William and Lambrinos 1985) and (Cervini-Pla, Silva, and Castello 2015). This lack of significant correlation of disability on wages is caused by selectivity bias [3]. Selectivity bias is when the effect of a portion of the sample is not represented in the change in the dependent variable. Simply put, the sample used for this research is not representative of the population intended to be analyzed. This occurs because the earnings of disabled people who do not work are not represented in the disabled category due to their earnings being missing in the data. Another example of selection bias is in an earnings regression when analyzing age on wages. Because of age discrimination in the workplace some people are not working due to age, from being laid off or age caps or not being able to find a new job. This group of people who are not working due to age discrimination are not represented in the wage data because they are not incurring any wages. The proper randomization of the data is not

3. Further information on what selectivity bias is and its use in a similar disabled earnings regression model can be found in (Marjorie and William 1994) and (William and Lambrinos 1985)

achieved due to the lack of wages in a certain group of people.

Table 2 presents the descriptive statistics of the original sample of data, presenting the 37,244 non-disabled people in Column 1 and the 1,301 disabled people in Column 2. Whether or not the mean of the variable is statistically different from the non-disabled to the disabled data is provided in Column 3. The average hourly wage is larger for non-disabled people compared to disabled people, which was expected. Non-disabled workers also use computers more than disabled workers on average. As people age they often experience an increasing amount of health problems. In accordance with this, the average age for disabled is almost eight years higher than the average age of the non-disabled observations. The average hourly wage and computer use are both statistically different from Column 1 to 2. The majority of the average occurrence of the controls are also statistically different from non-disabled to disabled, except for *Some College*, *Black*, *Other*, and *Female*. These other averages may not be statistically different because the disabled and non-disabled samples may have a proportionate amount of those groups of people in the data.

This sample selection bias issue has occurred in previous literature and was dealt with by the use of a Heckman Selection Model [4] (Marjorie and William 1994) and (William and Lambrinos 1985). The way the Heckman model accounts selection bias is by creating a new instrumental variable, λ. This variable represents the portion of the missing sample or the disabled workers who do not earn any money due to their disability. This λ variable is then used in a final Heckman regression, accounting for the effect disabled people not working on wage. The Heckman model runs two stages of regressions, the first stage or Heckman-Probit and the final stage or Heckman-OLS. In the Heckman-probit stage this λ variable is calculated by capturing the change in wage that is due to the missing wages of disabled people and is not able to be explained by the other independent variables. In the second stage of the Heckman regression the λ

4. An in depth discussion and description of the Heckman Selection Model can be found in chapter five in Rodgers, Marjorie, and William (2006). Chapter five describes the cases in which a selection model should be used and how to fit a model into a Heckman model.

variable created is then added into the regression. With this λ variable added in the regression selectivity bias is no longer an issue because the group of disabled people who were not being accounted for in the wage regression are included.

The four main models are used in regressions include only disabled, only specific disability, disabled and computer use interaction, and specific disability and computer use interaction variables. The four main models used in this project all include controls. In addition to running the full econometric model, a model was also run only using specific groups from the whole data sample. One sample created captures only the working people, which allowed the occupation fixed effects, industry fixed effects, and *Union* variables to be included in a regression. Various regressions were run with different specific groups of the sample. Some of the specific samples used in different regressions separated the observations by gender and or disability.

V Results

The data used in this study was pooled cross-sectional data from the Computer and Internet Use Supplemental Survey. The Computer and Internet Use Supplement is a part of the Current Population Survey, which is conducted by the Bureau of Labor Statistics. This survey supplement is administered to random U.S. citizens every other year and started in 2009, but in 2011 the supplement was altered to accommodate for the changes in technology. When studying disabled people and their income, the people who do not work because of their disability need to be considered. This group of people is not necessarily left out of the sample of people who are interviewed, but they are not represented in the disabled and non-disabled workers sample. With this sample OLS and all weighted regressions will produce biased results. The whole sample was expanded to include self-employed workers, people who earn zero dollars, and people who work zero hours.

The sample is tested in two groups based on for each gender, one table for male and one for female. Each table presents results from regular OLS regressions and Heckman-OLS regressions. For the OLS regressions a model with disabled and a model with disabled and computer use interaction are presented in Columns 1 and 2 respectively. The Heckmen-OLS results are presented for all four of the main models. Columns 3 and 4 present the Heckman disabled and disabled and computer use interaction regression results respectively (in Table 3 and 4). Columns 5 and 6 present the specific disability and specific disability interaction regression results respectively. In all of the results presented controls are included in the models. These controls are all significant at the one percent level, as shown in Table 3. Across all of the columns in Table 3 the results for the controls are robust [5].

The results of the male OLS and Heckman-OLS are presented in Table 3. When running OLS regressions on hourly wage disabled did have a significant effect at one percent, as shown in Column 1. However, Column 2 shows when running OLS regressions on hourly wage disabled only had a marginally significant [6] effect, at ten percent significance. The disabled results were not robust in the base OLS regressions because when the computer use and computer use disability interaction terms were added the disabled variable lost significance. When the Heckman model is incorporated results are robust for disability. Disabled workers earn significantly less than their non-disabled counterparts. In Column 3, the disabled variable is significant at the one percent level. When the disabled computer use interaction term is added, in Column 4, disability retained its significance and was robust across the regressions. The general disability computer use interaction term did not appear to have any significance in the OLS or the Heckman-OLS regressions, as shown in Columns 2 and 4. The selfcare disability and computer use interaction term is significant at the

5. Robust results, to put simply, are when the significance (of the results) is consistent across multiple tests.

6. Marginal significance is when the coefficients or marginal effects presented in the results are only significant on the ten percent level.

one percent level. The selfcare specific disabled variable also is significant at the five percent level. These results suggest that disabled people with selfcare issues that use computers earn significantly more than selfcare disabled people that do not use computers.

The results of the male OLS and Heckman-OLS are presented in Table 4. The OLS results for disabled show to only be marginally significant in Column 1. When the disabled and computer use interaction term is added to the model the disability variable loses all significance, as shown in Column 2. The disabled variable in the male Heckman results are consistent with those of the female results. The disability variable's coefficient is at the one percent significance level and are robust across Column 3 and 4. These results provide evidence that being disabled reduces the average hourly wage of disabled workers. The disabled and computer use interaction term is not significant in Table 3, as it is in Table 3. The selfcare disability and computer use interaction term is also significant at the one percent level and was robust across Table 3 and 4. The selfcare specific disabled variable also is significant at the five percent level and is robust across female and male results. Similar to Table 3, the results for the controls in the male sample, Table 4, are also significant at the one percent level. The results for the controls in table four shows robustness across the different regressions. The regression results for the female sample, Table 3, have higher over all significance compared to the male results, shown in Table 4. On average the female regression results have a higher magnitude compared to the male regression results.

The impact of disability on wages is consistent with the results of the various previous research Cervini-Pla, Silva, and Castello (2015), Jolly (2013), Anton, Brana, and Munoz de Bustillo (2016) and Albert et al. (2015). Also the results are consistent with those from (Basas 2013), however the method of analyzing the question and the model used were drastically different. Basas (2013) focus on the types of technological accommodation that can be provided to disabled workers and how those may help them in the work place. However, as to gain a better understanding on the impact of computer use on disabled workers, specifically disabled income, it is more appropriate to investigate the effect of computer use on disabled hourly wages.

VI Conclusions

VI.I Summary of the Findings

Using pooled cross-sectional data from the Current Population Survey, this study investigates whether computer use in the work place helps disabled workers earn more. In contrast to previous studies in the literature, this study examines how much a factor that helps disabled, specifically computer use, affects wage and corrects for sample selection bias.

This study finds that computer use does in fact have a significant positive effect on the income of disabled workers with *Selfcare* issues. It is hard to explain the correlation between computer use and *Selfcare* disabled people. The *Selfcare* disability variable represents when someone cannot dress or bathe himself or herself. There is no clear logical or economic reason that disabled people with this specific issue would significantly benefit from computer use. However, results also show that computer use does not significantly affect the wages of disabled people when considering the general disabled term. Also across regressions these results are not completely robust, meaning in some regressions the *Selfcare* and computer use interaction term is not significant. There are no concrete policy implications that can be made from the results of this research. Policy implications are hard to develop with the lack of robust results as well as lack of economic and rational theories and explanations to support the findings.

VI.II Limitations

The results of this analysis can be improved by obtaining more information about disabled workers. The specific disability variables only break down into six different specifics, but it could be broken down into much more descriptive and useful disability variables. Also the computer use variable may not have successfully captured computer use in the work place. If computer use were broken down further into types of computer use in the workplace the results would be more accurate. The more classifications of the computer use variable would provide a more accurate depiction of computer use in the workplace.

VI.III Suggestions for Future Research

Stemming off of this research future work on this subject should examine the group of people who suffer from a *Selfcare* disability. Specifically, what kind of job these people end up in, where they live, and what is the correlation between computer use and wages in that industry or occupation. Also further research into the severity of this disability could be important to determine how effective computer use really is with helping *Selfcare* disabled people earn more. Other research could attempt to develop theories that support the results found in this research.

Other future research could look into other factors that could counteract the wage gap caused by discrimination of disabled people. Some of these factors could include use of other accommodative technology or use of service dogs. These variables should be added, to a similar style model as used in my research, separately and include an interaction term between them to analyze their effect on disabled earnings. Also if data was found that provided more specific disability terms, as well as information on wages and computer use, they could be included in the same regression as the one conducted in this research. Using these more specific disability terms this could allow us to find significant correlations between other specific disabilities and computer use on wages.

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Table 2: Descriptive Statistics for Disabled and Non-Disabled Observations

Variable	(1) **NonDisabled**	(2)**Disabled**	(3) **Statistically Different**
Hourly Wage	21.769	20.012	✓
	(15.405)	(22.501)	
Computer Use	.581	.478	✓
	(.493)	(.450)	
Age	40.722	48.495	✓
	(13.866)	(15.661)	
Education Level			
High School	.270	.353	✓
	(.444)	(.478)	
Some College	.295	.315	✗
	(.456)	(.465)	
More College	.347	.230	✓
	(.476)	(.421)	
Race			
White	.649	.721	✓
	(.477)	(.449)	
Black	.111	.097	✗
	(.315)	(.300)	
Hispanic	.163	.122	✓
	(.369)	(.328)	
Other	.076	.059	✗
	(.266)	(.236)	
Female	.479	.446	✗
	(.500)	(.497)	
Metro	.863	.803	✓
	(.344)	(.398)	
Married	.518	.406	✓
	(.500)	(.491)	
Deaf		.328	N/A
		(.470)	
Blind		.150	N/A
		(.357)	
Memory		.263	N/A
		(.441)	
Physical		.395	N/A
		(.489)	
Selfcare		.060	N/A
		(.354)	
Errands		.137	N/A
		(.344)	
Number of Observations	37,244	1,301	

Note: The reported values are means. The standard deviations are presented within parenthesis.

Table 3: Female OLS and Heckman Regression Results on Log Hourly Wage

Variables	(1) OLS Disabled	(2) OLS Disabled x Computer Use	(3) Heckman Disabled	(4) Heckman Disabled x Computer Use	(5) Heckman Specific Disability	(6) Heckman Specific Disabilities x Computer Use
Computer Use		-0.089***		0.179***		0.180***
		(0.010)		(0.011)		(0.011)
Disabled	-0.086***	-0.076*	-0.134***	-0.128***		
	(0.029)	(0.041)	(0.030)	(0.044)		
Disabled*ComputerUse		-0.020		0.004		
		(0.057)		(0.060)		
Deaf					-0.087	-0.023
					(0.076)	(0.110)
Blind					0.012	0.120
					(0.107)	(0.108)
Memory					-0.175***	-0.219***
					(0.059)	(0.079)
Physical					-0.077*	-0.001
					(0.042)	(0.067)
Selfcare					-0.092	-0.532**
					(0.152)	(0.238)
Errands					-0.007	-0.030
					(0.077)	(0.095)
Deaf*ComputerUse						-0.124
						(0.148)
Blind*ComputerUse						-0.234
						(0.201)
Memory*ComputerUse						0.112
						(0.113)
Physical*ComputerUse						-0.136
						(0.083)
Selfcare*ComputerUse						0.809***
						(0.296)
Errands*ComputerUse						0.109
						(0.159)
Age	0.027***	0.026***	0.045***	0.042***	0.045***	0.042***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
AgeSq	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
High School	0.096***	0.090***	0.182***	0.157***	0.181***	0.156***
	(0.017)	(0.017)	(0.018	(0.018)	(0.018	(0.017)
Some College	0.146***	0.126***	0.294***	0.234***	0.293***	0.233***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
More College	0.429***	0.400***	0.720***	0.633***	0.719***	0.632***
	(0.019)	(0.019)	(0.018)	(0.018)	(0.018)	(0.018)
Black	-0.072***	-0.065***	-0.087***	-0.071***	-0.086***	-0.071***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Hispanic	-0.097***	-0.087***	-0.127***	-0.103***	-0.127***	-0.103***
	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)
Other	-0.041***	-0.036***	-0.081***	-0.065***	-0.080***	-0.064***
	(0.020)	(0.020)	(0.021)	(0.021)	(0.021)	(0.021)
Metro	0.089***	0.088***	0.107***	0.100***	0.106***	0.100***
	(0.012)	(0.012)	(0.013)	(0.013)	(0.012)	(0.012)
Married	0.042***	0.038***	0.053***	0.044***	0.053***	0.043***
	(0.009)	(0.009)	(0.010)	(0.009)	(0.010)	(0.009)
rho			.072	.071	.071	.071
			(.017)	(.019)	(.016)	(.019)
lambda			.038	.038	.037	.037
			(.008)	(.010)	(.008)	(.010)
Occupation Fixed Effects	Y	Y	N	N	N	N
Industry Fixed Effects	Y	Y	N	N	N	N
State Fixed Effects	Y	Y	Y	Y	Y	Y
Yearly Fixed Effects	Y	Y	Y	Y	Y	Y

Note: The standard errors are presented in parenthesis. For the Heckman regressions the values in the table represent the coefficients for each independent variable. All of the regressions are weighted according to the outgoing rotational weights provided by the Current Population Survey. Statistically significant results at the 0.10, 0.05, and 0.01 level are shown as *, ** and *** respectively.

Table 4: Male OLS and Heckman Regression Results on Log Hourly Wage

Variables	(1)OLS Disabled	(2) OLS Disabled x Computer Use	(3) Heckman Disabled	(4) Heckman Disabled x Computer Use	(5) Heckman Specific Disability	(6) Heckman Specific Disabilities x Computer Use
Computer Use		-0.093***		0.179***		0.180***
		(0.010)		(0.011)		(0.011)
Disabled	-0.039*	-0.041	-0.111***	-0.128***		
	(0.024)	(0.032)	(0.026)	(0.044)		
Disabled*ComputerUse		-0.010		0.004		
		(0.048)		(0.060)		
Deaf					0.003	-0.023
					(0.043)	(0.110)
Blind					-0.020	0.120
					(0.066)	(0.108)
Memory					-0.155***	-0.219***
					(0.057)	(0.079)
Physical					-0.144***	-0.001
					(0.044)	(0.067)
Selfcare					-0.025	-0.532**
					(0.136)	(0.238)
Errands					-0.019	-0.030
					(0.101)	(0.095)
Deaf*ComputerUse						-0.124
						(0.148)
Blind*ComputerUse						-0.234
						(0.201)
Memory*ComputerUse						0.112
						(0.113)
Physical*ComputerUse						-0.136
						(0.083)
Selfcare*ComputerUse						0.809***
						(0.296)
Errands*ComputerUse						0.109
						(0.159)
Age	0.036***	0.036***	0.059***	0.057***	0.059***	0.057***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
AgeSq	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
High School	0.208***	0.200***	0.265***	0.157***	0.264***	0.156***
	(0.014)	(0.014)	(0.014)	(0.018)	(0.014)	(0.017)
Some College	0.267***	0.243***	0.368***	0.311***	0.368***	0.311***
	(0.014)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
More College	0.511***	0.478***	0.738***	0.649***	0.737***	0.649***
	(0.017)	(0.017)	(0.016)	(0.017)	(0.016)	(0.017)
Black	-0.143***	-0.145***	-0.194***	-0.177***	-0.193***	-0.176***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Hispanic	-0.110***	-0.100***	-0.133***	-0.112***	-0.132***	-0.111***
	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)
Other	-0.064***	-0.056***	-0.084***	-0.070***	-0.084***	-0.070***
	(0.018)	(0.018)	(0.019)	(0.019)	(0.019)	(0.019)
Metro	0.028**	0.024**	0.109***	0.026***	0.059***	0.027***
	(0.011)	(0.011)	(0.023)	(0.011)	(0.002)	(0.011)
Married	0.081***	0.076***	0.163***	0.115***	-0.001***	0.115***
	(0.009)	(0.009)	(0.019)	(0.010)	(0.000)	(0.010)
rho			.099	.089	.100	.090
			(.012)	(.013)	(.012)	(.012)
lambda			.053	.047	.053	.046
			(.006)	(.007)	(.006)	(.006)
Occupation Fixed Effects	Y	Y	N	N	N	N
Industry Fixed Effects	Y	Y	N	N	N	N
State Fixed-Effects	Y	Y	Y	Y	Y	Y
Yearly Fixed-Effects	Y	Y	Y	Y	Y	Y

Note: The standard errors are presented in parenthesis. For the Heckman regressions the values in the table represent the coefficients for each independent variable. All of the regressions are weighted according to the outgoing rotational. Statistically significant results at the 0.10, 0.05, and 0.01 level are shown as *, ** and *** respectively.

Appendices

A Tables

Table 5: Male and Female Heckman-Probit results Model 1

Variables	(1)Heckman-Probit Male	(2) Heckman-Probit Female
Disabled	-0.842***	-0.842***
	(0.032)	(0.032)
Age	0.111***	0.111***
	(0.003)	(0.003)
Age^2	0.001***	0.001***
	(0.000)	(0.000)
High School	0.349***	0.485***
	(0.027)	(0.029)
Some College	0.438***	0.602***
	(0.028)	(0.029)
More College	0.565***	0.734***
	(0.029)	(0.030)
Black	-0.189***	-0.066**
	(0.029)	(0.027)
Hispanic	0.201***	-0.036
	(0.028)	(0.026)
Other	0.046	0.129***
	(0.033)	(0.032)
Metro	0.109***	0.024
	(0.023)	(0.022)
Married	0.163***	-0.261***
	(0.019)	(0.017)
State Fixed-Effects	Y	Y
Yearly Fixed-Effects	Y	Y

Note: The reported values are means. The standard deviations are presented within parenthesis. All of the regressions are weighted according to the final annual weights provided within the Current Population Survey data. Statistically significant results at the 0.10, 0.05, and 0.01 level are shown as *, ** and *** respectively.

Table 6: All Heckman Regression Results for Male and Female

Variables	(1) Disabled	(2) Specific Disability	(3) Disabled x Computer Use	(4) Specific Disabilities x Computer Use
Computer Use			0.173***	0.173***
			(0.007)	(0.007)
Disabled	-0.121***		-0.117***	
	(0.020)		(0.028)	
Disabled*Computer Use			0.022	
			(0.039)	
Deaf		-0.019		-0.027
		(0.038)		(0.049)
Blind		-0.006		0.062
		(0.062)		(0.071)
Memory		-0.167***		-0.177***
		(0.042)		(0.060)
Physical		-0.110***		-0.067
		(0.030)		(0.044)
Selfcare		-0.055		-0.343**
		(0.105)		(0.143)
Errands		-0.017		0.023
		(0.062)		(0.079)
Deaf*ComputerUse				0.015
				(0.075)
Blind*ComputerUse				-0.148
				(0.121)
Memory*Computer Use				0.038
				(0.079)
Physical*Computer Use				-0.067
				(0.059)
Selfcare*Computer Use				0.586***
				(0.199)
Errands*Computer Use				0.022
				(0.129)
Age	0.053***	0.053***	0.050***	0.050***
	(0.001)	(0.001)	(0.001)	(0.001)
AgeSq	-0.001***	-0.001***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
High School Education	0.232***	0.231***	0.209***	0.208***
	(0.011)	(0.011)	(0.011)	(0.011)
Some College Education	0.339***	0.338***	0.280***	0.279***
	(0.011)	(0.011)	(0.011)	(0.011)
More College Education	0.737***	0.736***	0.649***	0.648***
	(0.012)	(0.012)	(0.012)	(0.012)
Black	-0.135***	-0.134***	-0.119***	-0.118***
	(0.011)	(0.011)	(0.011)	(0.011)
Hispanic	-0.131***	-0.131***	-0.109***	-0.109***
	(0.010)	(0.010)	(0.010)	(0.010)
Other	-0.084***	-0.084***	-0.069***	-0.068***
	(0.014)	(0.014)	(0.014)	(0.014)
Female	-0.192***	-0.191***	-0.196***	-0.195***
	(0.006)	(0.006)	(0.006)	(0.006)
Metro	0.070***	0.070***	0.062***	0.062***
	(0.009)	(0.009)	(0.009)	(0.009)
Married	0.089***	0.089***	0.079***	0.078***
	(0.007)	(0.007)	(0.007)	(0.007)
State Fixed-Effect	Y	Y	Y	Y
Year Fixed-Effects	Y	Y	Y	Y
Observations	112,056	112,056	112,056	112,056

Note: The standard errors are presented in parenthesis. For the Heckman regressions the values in the table represent the coefficients for each independent variable. All of the regressions are weighted according to the outgoing rotational weights provided by the Current Population Survey. All regression models ran included state fixed effects and yearly fixed effects. All of the regressions are weighted according to the final annual weights provided within the Current Population Survey data. Statistically significant results at the 0.10, 0.05, and 0.01 level are shown as *, ** and *** respectively.

B Glossary

Table 7: Description of Specific Disability Variables Table

Specific Disability Variable	Description
Deaf	1 if the person is Deaf or has serious difficulty hearing ; 0 otherwise
Blind	1 if the person is Blind or has serious difficulty seeing when wearing glasses ; 0 otherwise
Memory	1 if person is has serious difficulty remembering, concentrating or making decisions due to a physical, mental or emotional condition; 0 otherwise
Physical	1 if the person has serious difficulty walking or climbing stairs; 0 otherwise
Selfcare	1 if the person has serious difficulty dressing or bathing; 0 otherwise
Errands	1 if the person has serious difficulty doing errands alone such as shopping or visiting a doctors officedue to a physical, mental or emotional condition; 0 otherwise; 0 otherwise

C Equations

1. Secondary Econometric Heckman Model to Estimate the Correlation between income and use of technology by specific disabled categories to examine the effect of use of technology on the income of workers with specific disabilities, this study uses the following econometric model:

$$
\begin{aligned}
\text{LogHourlyWage} = \beta_0 &+ \beta_1 \text{Computer Use} \\
&+ \beta_2 \text{Blind} + \beta_3 \text{Deaf} + \beta_4 \text{Memory} \\
&+ \beta_5 \text{Physical} + \beta_6 \text{Self Care} + \beta_7 \text{Errands} \\
&+ \beta_8 \text{Blind * Computer Use} + \beta_9 \text{Deaf * Computer Use} \\
&+ \beta_{10} \text{Memory * Computer Use} + \beta_{11} \text{Physical * Computer Use} \\
&+ \beta_{12} \text{Selfcare * Computer Use} + \beta_{13} \text{Errands * Computer Use} \\
&+ \beta_{14} \text{Age} + \beta_{15} \text{Age}^2 \\
&+ \beta_{16} \text{Education} + \beta_{17} \text{Race} + \beta_{18} \text{Gender} \\
&+ \beta_{19} \text{Married} + \beta_{20} \text{Metro} \\
&+ \beta_{21} \text{State dummies} + \beta_{22} \text{Year dummies} + \epsilon
\end{aligned}
$$

where ϵ is a stochastic disturbance term.

2. Primary Econometric Model to Estimate the Correlation between income and disabled to examine the effect of being disabled on hourly wages, this study uses the following econometric model:

$$
\begin{aligned}
\text{LogHourlyWage} = \beta_0 + \beta_1 &\text{Disabled} \\
&+ \beta_{14}\text{Age} + \beta_{15}\text{Age}^2 \\
&+ \beta_{16}\text{Education} + \beta_{17}\text{Race} + \beta_{18}\text{Gender} \\
&+ \beta_{19}\text{Married} + \beta_{20}\text{Metro} \\
&+ \beta_{21}\text{State dummies} + \beta_{22}\text{Year dummies} + \epsilon
\end{aligned}
$$

where ϵ is a stochastic disturbance term.

3. Secondary Econometric Model to Estimate the Correlation between income and specific disability variables to examine the effect of the specific disabilities on hourly wages, this study uses the following econometric model:

$$\begin{aligned}
\text{LogHourlyWage} = \beta_0 &+ \beta_1\text{Computer Use} \\
&+ \beta_2\text{Blind} + \beta_3\text{Deaf} + \beta_4\text{Memory} \\
&+ \beta_5\text{Physical} + \beta_6\text{Self Care} + \beta_7\text{Errands} \\
&+ \beta_8\text{Blind * Computer Use} + \beta_9\text{Deaf * Computer Use} \\
&+ \beta_{10}\text{Memory * Computer Use} + \beta_{11}\text{Physical * Computer Use} \\
&+ \beta_{12}\text{Selfcare * Computer Use} + \beta_{13}\text{Errands * Computer Use} \\
&+ \beta_{14}\text{Age} + \beta_{15}\text{Age}^2 \\
&+ \beta_{16}\text{Education} + \beta_{17}\text{Race} + \beta_{18}\text{Gender} \\
&+ \beta_{19}\text{Married} + \beta_{20}\text{Metro} \\
&+ \beta_{21}\text{State dummies} + \beta_{22}\text{Year dummies} + \epsilon
\end{aligned}$$

where ϵ is a stochastic disturbance term.