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The determinants of wages among disabled Americans in non-STEM and STEM occupations

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Abstract.
BACKGROUND: More than 1 in 4 adult Americans have a disability limiting their daily functioning to earn living wages. Meanwhile, the shortage of U.S. professionals in STEM fields persists because of underrepresentation of specific groups, such as racial and ethnic minorities, women, and people with disabilities.
OBJECTIVE: The study investigates the determinants of wages among Americans with disabilities in non-STEM and STEM occupations to explore the feasibility of broadening their participation in STEM careers where they may earn higher wages and thereby, close the wage-gap with their non-disabled peers.
METHODS: The study used a research design based on Mincer's earnings regression model to analyze select variables as wage determinants based on data from the 2018 American Community Survey (ACS).
RESULTS: While the findings suggest that within the Americans with disabilities group, working in a STEM occupation with a college degree in a STEM field was the best route to attain maximum wages, significant wage disparities exist compared to Americans without disabilities.
CONCLUSION: The implications of the findings for Vocational Rehabilitation providers are discussed.

Keywords: Americans, disabilities, employment, STEM occupations, wages

1. Introduction

More than thirty years ago on July 26, 1990, President George H.W. Bush signed into law the Americans with Disabilities Act (ADA) to guarantee equal protection for people with a range of disabilities, from mental health issues to physical challenges. Modeled after the 1964 Civil Rights Act, the ADA prohibits discrimination against people with disabilities in areas such as employment, transportation and public accommodations. Three decades after its passage, however, disabled Americans still face higher unemployment than non-disabled working adults, a problem only further compounded by the coronavirus pandemic. More than 1 in 4 adult Americans have a disability limiting their daily functioning to earn living wages (Okoro et al., 2016). According to the U.S. Bureau of Labor Statistics (2021), 17.9 percent of persons with a disability were employed in 2020, down from 19.3 percent in 2019. For persons without a disability, 61.8 percent were employed in 2020, down from 66.3 percent in the prior year. The unemployment rates for persons with and without a disability both increased from between 2019 and 2020 to 12.6 percent and 7.9 percent, respectively.

Meanwhile, the shortage of U.S. professionals in STEM fields persists because of underrepresentation of specific groups, such as racial and ethnic

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minorities, women, and people with disabilities (National Center for Science and Engineering Statistics, 2021). There are many factors why this is the case (see Fry et al., 2021). Specifically, when compared to their nondisabled peers, working adults with disabilities are less likely to earn a college degree—and even less so in a STEM field and therefore, less qualified for jobs in STEM occupations (U.S. Bureau of Labor Statistics, 2021). Yet, the earnings premium for a STEM degree can be as much as 24 to 27 percent, which could lead to improved standards of living for many disabled Americans (National Science Board, 2021, p. 39). In 2019, the average wage with a STEM Bachelor's degree or higher was $78,000 compared to $53,000 for non-STEM jobs—a difference of $25,000 representing a 47.2 percent premium. Without a college degree, the average wage was $43,200 for STEM jobs compared to $27,000 for non-STEM positions, a difference of $16,200 representing a 60 percent premium (National Science Board, 2021, p. 37). Employment in STEM fields is also widely considered to be among the most desirable because of its relative stability compared to other occupations (Torres-Olave, 2019).

Nonetheless, the case for the current study derives from the most recent findings on persons with disabilities in science and engineering, published by researchers at the National Center for Science and Engineering Statistics (NCSES, 2021). They found that about 10 percent of women and about 9 percent of men who were scientists and engineers with at least a bachelor's degree were not working due to chronic illness or disability (p. 36). Moreover, their results indicated scientists and engineers with disability had a higher unemployment rate than those without disability—even higher than the overall U.S. unemployment rate in 2019 (p. 39). Of those employed as scientists and engineers with at least a bachelor's degree, males had a higher disability rate than females, and underrepresented minorities had a higher disability rate compared to Whites or Asians (p. 38). The researchers also indicated that among employed scientists and engineers with a disability, a smaller share worked in STEM occupations, while a larger share worked in non-STEM occupations than those without disability (p. 40). In their conclusions, the NCSES researchers cited the need to further investigate the employment of those with disabilities to better understand their representation in STEM occupations (p. 54).

The current study contributes to this call for further research to investigate the employment of those with disabilities to better understand their representation in STEM occupations. To do so, the current study purposefully investigates the determinants of wages among Americans with disabilities in non-STEM and STEM occupations to explore the feasibility of broadening their participation in STEM careers where they may earn higher wages and thereby, close the wage-gap with their non-disabled peers.

1.1. Workplace disparities for people with disabilities

Several studies have documented the lower earning power of workers with disabilities, after controlling for education and other personal characteristics (e.g., Baldwin & Choe, 2014; Jones, 2008; Kruse et al., 2018), and appear in longitudinal comparisons of before and after the onset of disability among those who become re-employed (e.g., Butler et al., 2006; Pransky et al., 2016). Studies also find other disparities in important job outcomes for workers with disabilities. For example, some studies cite that workers with disabilities have lower levels of perceived job security and experience layoffs more often than those without disabilities (e.g., Mitra & Kruse, 2016).

In addition, workers with disabilities are less likely to access employer-provided benefits like health insurance, retirement plans, and employer-provided training (e.g., Lustig & Strauser, 2004). More often, they are also likely to be in part-time, temporary, and other non-standard jobs that pay low wages and provide few benefits (e.g., Jones, 2007; Schur, 2003). Given these disparities in job outcomes, workers with disabilities commonly report lower levels of job satisfaction than workers without disabilities (e.g., Jones, 2016; Uppal, 2005).

Researchers have suggested labor market explanations for these workplace disparities facing people with disabilities. The lower employment rates of people with disabilities may occur if their reservation wage (i.e., the lowest wage a person is willing to accept to be employed) is higher than the wages an employer is willing to offer. Under such conditions, there is a lower chance a person would take the job offer (French & Song, 2014). Another possible labor market explanation for workplace disparities among people with disabilities is that they may have different job preferences like a desire for flexible work arrangements and part time work compared to workers without disabilities (e.g., Jones, 2007). Under such circumstances, people with disabilities may accept lower pay in exchange for these job preferences (Ali et al., 2011).

Two other explanations of wage disparities among workers with disabilities are based on employer discrimination (Blanck, 2005). Proposed by Becker (1957), the taste-based discrimination model argues that an employer's prejudice or dislikes expressed in an organizational setting can have negative results in hiring minority workers, meaning the employer is said to have a "taste for discrimination". If so, prejudiced employers may refuse to hire applicants with disabilities to avoid personal, co-worker, and customer interaction with them—and this is regardless of their productivity (Scior, 2011).

Statistical discrimination is another model that may explain wage disparities of workers with disabilities (Phelps, 1972). Here, employers enact discrimination when—due to imperfect information about the individuals they interact with during the hiring process—they "statistically" infer productivity about the applicants based on their membership in a particular group. For example, if an employer believes that disabilities are associated with, on average, lower productivity, this may result in negative employment decisions when hiring individuals with disabilities (Rodgers, 2009, p. 223).

1.2. Current study theoretical framework

The current study uses human capital theory as the basis for the research. Human capital theory suggests that a worker's earnings are related, directly and solely, to the worker's productive capacity, i.e., human capital represented by an individual's particular set of skills, knowledge, and abilities (Becker, 1964). Workers can increase their wages by investing in human-capital-enhancing activities that, presumably, make them more productive and thereby qualified for higher paying jobs (Mincer, 1974). While human capital can take multiple forms (e.g., communication skills, technical skills, creativity, personal resilience), economists generally cite differences in the level of education as the explanation for observed labor market differentials between groups of workers. Even so, there is also strong evidence that returns to the same level of educational attainment are unequal between select groups of workers (Darity & Underwood, 2021). With this as the backdrop for the current study, the following questions guide the research.

- What contextual factors of employment moderate returns to wages in non-STEM and STEM occupations for workers with disabilities compared to non-disabled workers?
- How do non-STEM and STEM degrees at different levels of attainment mediate returns to wages in non-STEM and STEM occupations for workers with disabilities compared to non-disabled workers?
- To what extent are the returns to educational attainment unequal in non-STEM and STEM occupations for workers with disabilities compared to non-disabled workers?

In addressing these questions, the current study contributes to the labor market literature on wage disparities and based on the findings, offers recommendations to Vocational Rehabilitation providers to support individuals with disabilities as they prepare for, obtain, retain or advance in STEM employment. The next sections outline the method and results from the analysis, followed by a discussion of the findings and conclusions.

2. Method

2.1. Data sources

The Public Use Microdata Sample (PUMS) files for the 2018 American Community Survey (ACS) were the primary data source for the current study (U.S. Census Bureau, 2019a). The ACS was selected for the current study because it includes estimates of disability for smaller subgroups of the population (U.S. Census Bureau, 2022) and thereby, increased more accurately the number of respondents with disabilities that could be identified in non-STEM and STEM occupations. Under the direction of the U.S. Census Bureau, the ACS is an ongoing annual survey of information about the nation's people. The ACS PUMS files are a set of un-tabulated records about individual people or housing units. The U.S. Census Bureau produces the PUMS files so data users can create custom tables not available through pre-tabulated (or summary) ACS data products. There were two types of PUMS files: one for Person records and one for Housing Unit records (U.S. Census Bureau, 2019b). Each record in the Person file represented a single individual. Of the 3,214,539 Person records, 525,805 respondents were selected for the current study based on the criteria shown in Table 1.

Table 1
Data selection variables and values

Criteria	Variable	Value and definition
Respondent's Age	AGE	25 – 65 (numeric)
Citizenship Status	CIT	1 = Born in the US 2 = Born in Puerto Rico, Guam, the US Virgin Islands, or the Northern Marianas 3 = Born abroad of American parent(s) 4 = US citizen by naturalization
Class of Worker	COW	1 = Employee of a private for-profit company or business, or of an individual, for wages, salary, or commissions 2 = Employee of a private not-for-profit, tax-exempt, or charitable organization 3 = Local government employee (city, county, region) 4 = State government employee 5 = Federal government employee
Employment Status Record	ESR	1 = Civilian employed, at work
Survey Respondent – Relationship	RELP	'00' = Reference person (Self-reporting)
School Grade Attending	SCHG	'blank' = Not enrolled in school
Standard Occupational Code	SOCP	Non-STEM and STEM occupations*
When Last Worked	WKL	1 = Within the past 12 months

*Per U.S. Census Bureau and O*NET STEM SOC codes.

Given the criteria, the final ACS 2018 data selected consisted of self-reporting individuals (RELP) on the survey, between the ages of 25 and 65 (AGEP), with US citizenship status (CIT), not enrolled in college (SCHG), employed within the prior 12 months (WKL) in the private, non-profit, or public sectors (COW) as a civilian worker (ESR) in a non-STEM or STEM occupation (SOCP). The ACS data also provided a seven-digit Standard Occupational Classification (SOC) code, a federal statistical standard used by federal agencies to classify workers into occupational categories for collecting, calculating, or disseminating data. To identify the STEM occupations for the current study, the ACS data was then merged by SOC with STEM SOC codes from the U.S. Census Bureau (2018a) based on the STEM SOC codes from the U.S. Department of Labor's Occupational Information Network (National Center for O*NET Development, 2022a). Of the 923 occupations in the data collection, the O*NET defines over 100 as STEM-related (Fayer et al., 2017, p. 34). These include computer and mathematical, architecture and engineering, and life and physical science occupations, as well as managerial and postsecondary teaching occupations related to these functional areas, and sales occupations requiring scientific or technical knowledge at the postsecondary level.

2.2. Measures

The measures in the current study consisted of explanatory categorical indicators derived from ACS variables. Female, STEM Degree, and STEM Occupation were dichotomous variables coded a value of one for individuals indicating they were female, earned a STEM degree, or worked in the prior year in a STEM occupation, respectively. If not, the select variable was coded a zero. (Note: the ACS data only recognizes science degrees for Bachelors, Masters, Professional degrees, and Doctorate levels). Similarly, Hispanic, Black, Asian, and Other were dummy variables, coded a value of one for individuals indicating they were a member of the ethnicity group, and a value of zero if not a member. The Other Race category consisted of American Indian, Alaska Native, Native Hawaiian and Pacific Islander, and individuals of two or more races (U.S. Census Bureau, 2019b, 2019c, 2019d). White Americans were defined when Hispanic, Black, Asian, and Other variables all equaled zero. The ACS asks respondents about six disability types: hearing difficulty, vision difficulty, cognitive difficulty, ambulatory difficulty, self-care difficulty, and independent living difficulty (U.S. Census Bureau, 2022). The Disabled dichotomous variable was coded a one if the respondent reported anyone of the six disability types. Otherwise, the Disabled variable was coded zero. These reference groups were selected in the current study because of the known impact on wages from the intersectionality between disability, gender, and race/ethnicity (see Kozlowski, 2022).

For the education variable, the ACS survey allowed respondents to report their highest degree earned or the highest level of school completed (U.S. Census Bureau, 2019b, 2019c, 2019d). In the current study, respondents who received a General Educational Development (GED, ACS category 17) were first recoded as receiving a regular high school diploma (ACS category 16). The ACS education categories of 15 (12th grade or less) to 24 (Doctorate) were then renumbered zero to eight so that the education level of zero was 12th grade or less progressing to a value of 8 for the Doctorate level.

ACS data reported the number of weeks respondents worked during the past 12 months (U.S. Census Bureau, 2019b, 2019c, 2019d) organized into six progressive work-per-week levels. For the current study, the ACS Weeks/Year categories of one (<14 weeks) to six (50 to 52 weeks) were renumbered zero to five indicating six progressive weeks-per-year worked levels.

The ACS defined the public sector as government agencies (e.g., city police and fire departments) while the non-profit sector consisted of not-for-profit organizations like the Red Cross (U.S. Census Bureau, 2019b, 2019c, 2019d). Non-Profit and Public were dummy variables, coded a value of one for individuals indicating they worked in that sector during the prior year, and a value of zero if not employed in the sector. Americans working in the private sector were defined when both Non-Profit and Public variables equaled zero.

Thus, when these categorical variables equaled zero, the reference group for the current study consisted of White males, not disabled, non-STEM degreed with a 12th grade or less education level, and working in the private sector in a non-STEM occupation less than 14 weeks in the prior year. The current study specifically used White males as the reference group because STEM workers are disproportionately White and male representing one-half of the STEM workforce (McNeely & Fealing, 2018).

In addition to the measures based on categorical data, the explanatory continuous variables consisted of age (25 to 65 years old) and average hours-per-week worked in the prior year (1 to 99), as reported by respondents in the ACS (U.S. Census Bureau, 2019b, 2019c, 2019d). In the current study, the log of wages was the output measure calculated from the individual's self-reported annual wages earned where employed as a worker in the prior year (U.S. Census Bureau, 2019b, 2019c, 2019d).

2.3. Research design

The current study used a research design based on Mincer's (1974) earnings regression model, which in its initial form related the logarithm of wages to the level of education, years of work experience, and years of work experience squared. Researchers' critical overviews of early studies using Mincer's model recognized its power to statistically predict wages (e.g., Heckman et al., 2008). Since then, Mincer's earnings regression model has become the standard research method by labor market economists for the estimation of returns to human capital that include preferences and demographic characteristics of the individuals (see Mulyaningsih et al., 2021).

2.4. Analytic procedures

Following the convention in labor economics based on Jacob Mincer's framework (1974), the dependent variable in the following regression model was the natural logarithm of the annual wages output measure, which corrects for skewness in the earnings distribution.

$$\ln(\text{wages}) = \beta_0 + \beta_1 X_1 \ \ldots + \ldots$$

$$\beta_n X_n + \beta_{n+1}\text{Disabled} + \varepsilon$$

The intercept term, β_0, defined the regression constant. For a continuous predictor variable, its regression estimate β multiplied by 100 defined for a one-unit change in the predictor, a β percentage change of wages in monetary form, after holding all other covariates constant. In comparison, the following predictor variables required a transformation of the β estimates into β^* based on the equation, $\beta^* = e^{\beta} - 1 \times 100$ to interpret the β estimates in monetary form. For a dummy predictor variable, its regression estimate β^* defined the percentage change in wages in its monetary form relative to the median wages of the reference group when the predictor dummy-variable equaled one, and all other dummy variables equaled zero—after holding all other covariates constant. For a dichotomous predictor variable, its regression estimate β^* defined the percentage change in wages in its monetary form relative to the median wages of the reference group when the dichotomous variable equaled to zero, after holding all other covariates constant. Thus, if a regression parameter β (or β^*) estimate was positive, the percentage earnings resulted in a wage premium; if negative then the percentage earnings resulted in a discount. Random errors were captured in the term ε (Bazen, 2011).

The regression model included Age and Hours/Week in quadratic form, Age^2 and $Hours/Week^2$, respectively. This considers the possibility of the common presence in labor data of wages increasing at a decreasing rate with increasing age or hours-per-week worked. In doing so, the quadratic covariates in the regression model do not alter the interpretation of the findings but rather, allows for the calculation at what age between 25 and 65, and hours-per-week worked between 1 and 99 the wages maximize based on the following formula:

$$\text{Covariate at Maximum Salary} = (-100 \times \beta_p)$$

$$\div(2 \times \beta_q), \text{ where}$$

$$\beta_p = \text{ estimate for covariate, and}$$

$$\beta_q = \text{ estimate for quadratic covariate}$$

3. Results

3.1. A profile of Americans in the current study

Table 2 shows descriptive statistics for the selected ACS data. Based on the results, the following profile of Americans described the context of the current study. Of the 525,805 Americans in US occupations, 94.0 percent (n = 494,135) indicated no disability in the ACS survey. The average age among the Americans was 46.2 years (SD = 11.3 years). Of the 9 educational levels, 25.8 percent (n = 135,867) had a bachelor's degree. The primary ethnicity in the data was White, representing 75.1 percent (n = 395,000) of the Americans among the five ethnic groups. The gender distribution in the data was almost equal with 51.7 percent (n = 271,747) male and 48.3 percent (n = 254,058) female. Of the three sectors, 70.7 per-

Table 2
Descriptive statistics of wage regression model variables (N = 525,805 respondents)

Variable		Values/definitions			n	%
Disabled	0	No			494,135	94.0
	1	Yes			31,670	6.0
Education	0	12th grade or less			23,356	4.4
	1	High school/GED diploma			109,883	20.9
	2	Less than 1-year college			37,281	7.1
	3	1 + years college, no degree			72,370	13.8
	4	Associate			56,141	10.7
	5	Bachelor			135,867	25.8
	6	Masters			66,178	12.6
	7	Professional degree			14,818	2.8
	8	Doctorate			9,911	1.9
White	(Reference group)				395,000	75.1
Hispanic	0 = No, 1 = Yes				53,416	10.2
Black	0 = No, 1 = Yes				49,017	9.3
Asian	0 = No, 1 = Yes				23,083	4.4
Other	0 = No, 1 = Yes				5,289	1.0
Female	0	Male			271,747	51.7
	1	Female			254,058	48.3
STEM degree	0	No			439,094	83.5
	1	Yes			86,711	16.5
STEM occupation	0	No			437,063	83.1
	1	Yes			88,742	16.9
Private	(Reference group)				371,899	70.7
Public	0 = No, 1 = Yes				99,886	19.0
Non-profit	0 = No, 1 = Yes				54,020	10.3
Weeks/year	0	Less than 14 weeks			5,439	1.0
	1	14 to 26 weeks			6,041	1.2
	2	27 to 39 weeks			12,572	2.4
	3	40 to 47 weeks			20,335	3.9
	4	48 to 49 weeks			8,630	1.6
	5	50 to 52 weeks			472,788	89.9
		Mean	SD	Min	Median	Max
Age		46.2	11.3	25	47	65
Hours/week		41.9	10.2	1	40	99
Wages (unadjusted)		$68,304	$70,173	$4	$50,000	$718,000
Wages (exponentiated)		$48,212	$2	$4	$50,000	$717,997

Table 3
Descriptive statistics of disabled Americans education level by non-STEM and STEM occupations

	Non-STEM				STEM			
			Cumulative				Cumulative	
Education level	*n*	%	*n*	%	*n*	%	*n*	%
12th grade or less	2,350	8.5	2,350	8.5	45	1.2	45	1.2
High school/GED diploma	8,288	29.9	10,638	38.3	333	8.5	378	9.7
Less than 1-year college	2,807	10.1	13,445	48.4	259	6.6	637	16.3
1 + years college, no degree	4,692	16.9	18,137	65.3	590	15.1	1,227	31.4
Associate	2,985	10.8	21,122	76.1	721	18.5	1,948	49.9
Bachelor	4,186	15.1	25,308	91.2	1,213	31.1	3,161	81.0
Masters	1,901	6.9	27,209	98.0	505	12.9	3,666	93.9
Professional degree	314	1.1	27,523	99.1	144	3.7	3,810	97.6
Doctorate	242	0.9	27,765	100.0	95	2.4	3,905	100.0
All degrees BA+	6,643	23.9			1,957	50.1		
Non-STEM degrees (BA+)	4,452	76.1			972	49.1		
STEM degrees (BA+)	2,091	31.5			985	50.3		
Bachelor	1,202	57.5	1,202	57.5	567	57.6	567	57.6
Masters	627	30.0	1,829	87.5	260	26.4	827	84.0
Professional degree	138	6.6	1,967	94.1	98	10.0	925	93.9
Doctorate	124	5.9	2,091	100.0	60	6.1	985	100.0

cent ($n = 371{,}899$) of the Americans indicated they worked in the private sector. About 89.9 percent ($n = 472{,}788$) indicated the number of weeks worked in the prior year ranged from 50 to 52 weeks, and the average number of hours worked per week was 41.9 hours (SD = 10.2). Lastly, the average wage among the Americans was $68,304 (SD = $70,173), based on the selected ACS data.

Table 3 shows the distribution of disabled Americans by education level in non-STEM and STEM occupations further disaggregated by non-STEM and STEM degrees. Of the disabled Americans in non-STEM occupations, 23.9 percent ($n = 6{,}643$) held a Bachelor's degree or above with 31.5 percent ($n = 2{,}091$) in a STEM field. In STEM occupations, 50.1 percent ($n = 1{,}957$) of disabled Americans held a Bachelor's degree or above with 50.3 percent ($n = 985$) in a STEM field.

3.2. *The return to wages for Americans with disabilities*

The subsequent research was guided by the following question: What contextual factors of employment moderate returns to wages in non-STEM and STEM occupations for workers with disabilities compared to non-disabled workers? Table 4 organized the results from the wage regression model. All predictor variables indicated statistical significance at $p < .0001$ and represented about 53.0 percent of the variation in the model, as indicated by the adjusted R^2 value.

For the current study, the predictors were grouped into three categories. The least malleable variables were predictors where individuals cannot alter these wage determinants. The Age estimate indicated individuals earned, on average, a 5.8 percent increase for every year beyond 25 years of age, but at a decreasing rate of –5.4 percent with each year increase. Maximum salary calculated to 53.7 years of age. White Americans non-disabled were the reference group to the ethnicity dummy variables in the regression model. Asian Americans were the only ones with a positive parameter β estimate (0.051) indicating 5.2 percent higher wages than the reference group. The other three ethnic groups had negative parameter β estimates, indicating percentage discounts in monetary wages compared to White Americans. Here, Black Americans had the largest discount parameter β estimate (–0.161) followed by Americans from Other ethnicities (–0.152) and then by Hispanic Americans (–0.060), indicating percentage discounts in monetary wages of –14.9, –14.1, and –5.8, respectively. American males (non-disabled) were the reference group when the Female dichotomous variable equaled zero in the regression model. American females had a negative parameter β estimate (–0.245), indicating a percentage discount of –21.7 in monetary wages relative to American males.

The somewhat malleable variables were predictors where individuals have some possibility in altering these wage determinants. The Hours/Week estimate indicated individuals earn, on average, a 9.0 percent increase in wages, but at a decreasing rate of –6.8 percent with each additional hour. Maximum salary calculated to 66.2 hours-per-week. Weeks/Year pro-

Table 4
Wage regression model

Predictor	Est.	SE	t	p-value	%Wage change
Least malleable:					
Age (years)	0.058	0.0007	87.17	<.0001	5.8
$Age^2/100$	–0.054	0.0007	–74.14	<.0001	–5.4
Hispanic	–0.060	0.0029	–21.23	<.0001	–5.8
Black	–0.161	0.0030	–54.59	<.0001	–14.9
Asian	0.051	0.0042	12.32	<.0001	5.2
Other	–0.152	0.0085	–17.96	<.0001	–14.1
Female	–0.245	0.0018	–138.45	<.0001	–21.7
Somewhat malleable:					
Hours/week	0.090	0.0003	291.6	<.0001	9.0
$Hours/week^2/100$	–0.068	0.0003	–205.82	<.0001	–6.8
Weeks/year	0.258	0.0010	252.21	<.0001	29.4
Public	–0.030	0.0022	–13.41	<.0001	–3.0
Non-profit	–0.094	0.0029	–32.46	<.0001	–9.0
Disabled	–0.157	0.0036	–43.97	<.0001	–14.5
Most malleable:					
Education	0.127	0.0005	255.18	<.0001	13.5
STEM degree	0.118	0.0026	45.01	<.0001	12.5
STEM occupation	0.249	0.0024	104.94	<.0001	28.3
Constant	5.268	0.0160	330.17	<.0001	
Adjusted R-square	0.5298				
DF	16				
n	525,805				
Age (years) at max salary	53.7				
Hours/week at max salary	66.2				
Dependent median (Log)	10.81978				
Dependent median ($)	$50,000				

Note. The natural log of wages entered as the dependent variable in the model.

vided the largest premium regression parameter β (0.258), an increase of 29.4 percent in monetary wages for each unit increase in the categories shown in Table 2. Americans in the private sector were the reference group to the public and non-profit dummy variables in the regression model. Relative to the reference group, the results showed negative parameter β estimates for Americans working in the public (–0.030) and non-profit (–0.094) sectors, indicating percentage discounts in monetary wages of –3.0 and –9.0 percent, respectively.

As reported in the ACS data, the dichotomous Disabled predictor variable was coded zero if the individual indicated no disability and a value of one if any of the six disability types was reported (U.S. Census Bureau, 2022). The Disabled covariate variable shown in Table 4 was included in the somewhat malleable category because workers with disabilities have the possibility of increasing their productivity through accommodations and thereby their wages. Even so, the results showed a negative parameter β estimate (–0.157) for Americans with disabilities working in US occupations, indicating a percentage discount in monetary wages of –14.5 percent below non-disabled American males.

Next, the research was guided by the question: How do non-STEM and STEM degrees at different levels of attainment mediate returns to wages in non-STEM and STEM occupations for workers with disabilities compared to non-disabled workers? The most malleable variables were predictors where individuals have the greatest potential to alter these wage determinants. Working in a STEM occupation provided the largest premium regression parameter β (0.249)—a difference of 28.3 percent above the median salary of $50,000 earned by Americans across all occupations (see Table 2). Education level (0.127) and STEM degree (0.118) status also contributed a premium to the median monetary wage of 13.5 and 12.5 percent, respectively.

3.3. *Interpretation of the regression parameter estimates*

Lastly, the research was guided by the following question: To what extent are the returns to educational attainment unequal in non-STEM and STEM occupations for workers with disabilities compared to non-disabled workers? Table 5 illustrates how select regression parameter estimates translated as wage

Table 5
Wage multipliers by educational level for non-disabled/disabled Americans in non-STEM/STEM occupations per STEM degree status

Education level	Non-STEM occupation: No STEM degree	Non-STEM occupation: STEM degree	STEM occupation: No STEM degree	STEM occupation: STEM degree
	Americans without disabilities			
Bachelor	1.000*	1.144	1.201	1.375
Masters	1.188	1.359	1.427	1.633
Professional degree	1.411	1.614	1.695	1.940
Doctorate	1.676	1.918	2.014	2.304
	Americans with disabilities			
Bachelor	0.763	0.873	0.917	1.049
Masters	0.907	1.037	1.089	1.246
Professional degree	1.077	1.232	1.294	1.481
Doctorate	1.279	1.464	1.537	1.759
	Wage disparities			
Bachelor	–0.237	–0.271	–0.284	–0.326
Masters	–0.281	–0.322	–0.338	–0.387
Professional degree	–0.334	–0.382	–0.401	–0.459
Doctorate	–0.397	–0.454	–0.477	–0.545

Note. Reference shown (*) is 82,662 non-disabled workers, in the private sector, with a Bachelor degree, 43.7 years average age (SD = 11.3) and worked on average 43.6 hours/week (SD = 8.9), 50 to 52 weeks in the prior year earning a median wage of $73,130.

determinants by education level, under conditions of employment in non-STEM and STEM occupations with and without STEM degrees for Americans without disabilities compared to Americans with disabilities. To do so, the Mincer model was rerun with the log of wages regressed by Education, Disabled, STEM Degree, and STEM Occupation, after controlling for Age and Hours/Week where the Weeks/Year equaled 5 (i.e., worked 50 to 52 weeks in the prior year). Since the ACS only identifies STEM degrees at the Bachelor level and above, the Education levels were limited to these levels and recoded zero to three, so that zero represented the lowest education level in the model.

Having done so, the Table 5 entries represent wage multipliers relative to the reference group, calculated from exponentiating select regression estimates. Annotated in the table with an asterisk, the reference group consisted of 82,662 non-disabled workers, in the private sector, with a Bachelor degree, 43.7 years average age (SD = 11.3) and worked on average 43.6 hours/week (SD = 8.9), 50 to 52 weeks in the prior year earning a median wage of $73,130. Below the reference group, the entries show monetary wages based on a one-unit change in education level, after holding all other covariates constant. As a result, the reference group of non-disabled American workers can expect, for example, to increase their median base wages of $73,130 to $86,878 (median base wage x 1.188), if they earn a non-STEM Master's degree, and still higher wages at higher education levels. Put another way, if the reference group earned an annual salary of just one dollar (1.000 = $1.00), having a Masters, Professional, or Doctorate would increase their wages by 18.8 cents, 41.1 cents, and 67.6 cents, respectively.

The table then provides wage multiplier comparisons within the context of four workplace conditions for Americans with disabilities: working in (a) non-STEM occupations with no STEM degree, (b) non-STEM occupations with a STEM degree, (c) STEM occupations with no STEM degree, and (d) STEM occupations with a STEM degree. Across the four conditions, the table shows progressive wage multipliers at each education level. Compared to the reference group, for example, Americans without disabilities earn 1.144 more in wages with a STEM Bachelor's degree working in a non-STEM occupation. With a non-STEM Bachelor's degree, however, they can earn 1.201 more in wages working in a STEM occupation. Wages maximize with a multiplier of 1.375 if they have a STEM Bachelor's degree and work in a STEM occupation. Such a pattern can be seen at each education level and within each of the two groups: Americans without disabilities and Americans with disabilities.

Wage disparities emerged, however, when comparing the wage multipliers between the two groups for a given education level. For example, the wage multipliers of 1.375 and 1.049 for Americans without disabilities and Americans with disabilities, respectively, working with a STEM Bachelor's degree in a STEM occupation differs by –.326. Relative to the reference group's wages of $73,130, this means

Americans without disabilities make a median wage of $100,554 compared to $76,713 for Americans with disabilities—a wage disparity of $23,840.

Wage disparities also emerged between the two groups when comparing the wage multipliers among the education levels for a given workplace condition. For Americans with a STEM degree working in a STEM occupation, wage disparities between the two groups began at the Bachelor's degree level at –0.326 and progressively expanded by –0.386, –0.459, and –0.545 at the Master's, Professional, and Doctorate levels, respectively. This equates to progressive wage losses of –$23,840, –$28,301, –$33,567, and –$39,856 for Americans with disabilities.

Table 5 illuminates another finding related to wage disparities: the notion of non-equivalence of equivalents in education level between Americans without disabilities and Americans with disabilities. For example, Americans with disabilities with a STEM Doctorate degree working in a STEM occupation have a 1.759 wage multiplier as shown in Table 5, or $128,636 when multiplied by the reference group base wage ($73,130). For Americans without disabilities, this wage amount of $128,636 lies between the wage multipliers of a STEM Master's degree (1.633) and STEM Professional degree (1.940) education level, or between $119,421 and $141,872, respectively. In comparison, Americans without disabilities with a STEM Doctorate degree working in a STEM occupation earn $168,492 based on their wage multiplier of 2.304. Americans with disabilities must therefore earn higher education levels to compensate for losses in wages even with STEM degrees working in STEM occupations because their degree does not result in comparable wages for the degree at the same level held by Americans without disabilities.

4. Discussion

The current study investigated the determinants of wages among Americans with disabilities in non-STEM compared to STEM occupations, after controlling for characteristics defined by the predictor variables. The predictors were grouped into three categories. The least malleable variables were predictors where individuals could not alter these wage determinants. These findings related to Age, Gender, and the ethnicity/race covariates were consistent with prior studies (e.g., Benito et al., 2016; Fogg et al., 2018; Friedman & Rizzolo, 2020).

The somewhat malleable variables were predictors where individuals had some possibility in altering these wage determinants. In the current study, hours-per-week and weeks-per-year worked were two explanatory variables not commonly found in prior disability studies and therefore, a contributor to the literature by providing a more concise picture of wage differentials among disabled Americans. In comparison, the findings related to the sector variables were consistent with more recent labor market studies (e.g., Fogg et al., 2018). Americans working in the private sector earn higher wages than those working in the public and non-profit sectors. The Disabled covariate variable was included in the somewhat malleable category because workers with disabilities have the possibility of increasing their productivity through accommodations and thereby their wages (e.g., Padkapayeva et al., 2017; Telwatte et al., 2017). Even so, the results showed Americans with disabilities working in US occupations receive a percentage discount in monetary wages of –14.5 percent below non-disabled American males. Other prior labor market studies have shown similar disparities (e.g., Benito et al., 2016; Fogg et al., 2018; Friedman & Rizzolo, 2020).

The most malleable variables were predictors where individuals had the greatest potential to alter these wage determinants. The finding of education as a positive determinant to wages was consistent with prior studies (e.g., Benito et al., 2016; Fogg et al., 2018; Friedman & Rizzolo, 2020). Even so, augmenting the education level was STEM Degree, an explanatory dichotomous variable indicating if a degree earned was in a non-STEM or STEM field of study. This predictor was not commonly found in prior disability studies and therefore, a significant contributor to the literature by providing a more concise picture of education level as a wage differential among disabled Americans. Having a STEM degree at the Bachelor's level and above contributed a 12.5 percent premium to median monetary wages, after holding all other covariates constant.

A measure of whether Americans worked in a non-STEM or STEM occupation, the STEM Occupation dichotomous variable was another wage determinant not commonly found in prior disability studies and therefore, a contributor to the literature by providing a more concise picture of wage differentials among disabled Americans. Among the explanatory variables in the current study, the STEM Occupation dichotomous variable alone provided the second largest premium regression parameter β among all wage determinants, almost as large as the weeks-per-year worked parameter estimate. The findings indicated working in a STEM occupation—with or without a STEM degree—would result in 28.3 percent higher wages than working in a non-STEM occupation, after holding all other covariates constant.

4.1. Assumptions and limitations

These findings should be considered within the following assumptions and limitations: The ACS data for a given year represents approximately one percent of the United States population (U.S. Census Bureau, 2018b). For the current study, the estimates found were assumed to apply to the entire U.S. working population in non-STEM and STEM occupations.

The O*NET does not define a career pathway or degree major for an occupation, but rather by its knowledge, skills, and abilities, experience and prior training, credentials (e.g., licenses), job tasks, technology and tools used to perform the tasks, as well as the required level of education (National Center for O*NET Development, 2022b). The current study assumes these occupation characteristics were embedded in respondent's level of education and degree type (non-STEM or STEM) reported in the ACS and thereby, controlled for in the Mincer model.

Lastly, the current study acknowledges the limitations of the results from the absence of predictor variables in the Mincer model that might further explain the wage disparity findings. Categorical variables indicating type of disability (e.g., hearing, vision, cognitive), severity, and the onset occurrence of the disability (before or after entering the workforce) are examples of such predictors. Support for these variables comes from studies showing that wage returns can differ by the type of disability and are less for workers with more severe versus less severe disabilities (Jones, 2008), and for persons who become disabled early in life compared to those who become disabled as adults (Choe & Baldwin, 2017).

4.2. Implications for vocational rehabilitation providers

Based on the findings, the current study offers recommendations to Vocational Rehabilitation (VR) providers to support individuals with disabilities as they prepare for, obtain, retain or advance in STEM employment. Despite the disparities noted in the wage multipliers, VR providers should continue to inspire and guide individuals with disabilities to pursue a STEM degree or a career in STEM occupations because they earn higher wages than those with non-STEM degrees working in non-STEM occupations. For individuals with disabilities that do not want to pursue a STEM degree, VR providers should encourage them to pursue as much STEM education as available because the most recent research shows that STEM knowledge has become increasingly important even in non-STEM occupations (Cherrstrom et al., 2021).

The importance of education and training from vocational rehabilitation cannot be understated. Education is generally viewed as a pathway to professional work with good wages, benefits, and work conditions (Henly & Brucker, 2020). Education has both a direct effect on wages because education increases human capital, and an indirect effect because education decreases the probability of job mismatch for workers with physical disabilities. All else equal, workers with disabilities who find a good match (i.e., a job where their functional limitations have little or no impact on important job functions) have better employment outcomes than their counterparts who are mismatched (Choe & Baldwin, 2017).

For workers with disabilities to pursue STEM careers, they must not only acquire some level of STEM knowledge and abilities for a select occupation, but also develop the independent living skills required for workplace success. In this process, VR providers should make sure workers with disabilities learn to use computers, electronic communications, and internet resources to achieve their goals toward pursuing STEM careers (Henly & Brucker, 2020).

Developing social capital is another area where VR providers can assist workers with disabilities prepare for STEM occupations. Social capital enhances individual productivity in the workplace as well as facilitates socioeconomic upward mobility through skills that form personal relationships (Mau & Kopischke, 2001). First proposed by French sociologist Pierre Bourdieu (1977), the theory of social capital seeks to explain how differences in people's cultural resources—embodied in their knowledge and practices in social interactions such as social networks and relationships—create opportunities for social and financial advancement. Operationalized, his central thesis was that people acquire such social capital from their parents, which includes education, cultural knowledge, and language. People then deploy their cultural capital in social arenas to compete for positions of distinction and higher status (Webb et al., 2002). Hence, whereas physical capital refers to physical objects and human capital refers to the properties of individuals, social capital refers to connections among individuals that define the social networks and norms of reciprocity and trustworthiness arising from them (Portes, 1998).

People often underestimate the influence of their social capital because it stands in contrast to American society's attitudes rooted in the myth of individualism: the cultural belief that everyone should succeed or fail based on individual efforts and abilities (Baker, 2000, p. 2). But the cultural resources valued and rewarded in the workplace—that is, certain ways of being and talking, and common understandings—also reflects a dominant culture (Webb et al., 2002). Bourdieu's (1977) theory assumes that cultural capital includes familiarization with this dominant culture, with an emphasis on understanding and using educated language. This would be particularly important during the interview hiring process when negotiating and securing a competitive salary (Mau & Kopischke, 2001). The discrepancies in the wage multipliers suggest differences may exist in how well Americans with disabilities derive and use social capital to self-advocate in securing equal, competitive salaries compared to their non-disabled peers. If so, then this is where VR providers can prepare Americans with disabilities—in the development of social capital for the STEM job interview.

The current study provided a reference for realizing the feasibility of broadening the participation of disabled Americans in STEM careers where they may earn higher wages and thereby, close the wage-gap with their non-disabled peers. For the 2,091 disabled Americans shown in Table 3 with STEM degrees (BA+) working in non-STEM occupations, for example, there may be a possibility a STEM employer can transition them to a STEM occupation. They are the lowest hanging fruit for increasing disabled Americans in the STEM workforce. To put this into perspective, consider that the ACS data in the current study represented approximately one percent of the United States population (U.S. Census Bureau, 2018b). As a result, the estimate reported here could represent approximately 209,100 disabled Americans available for STEM occupations.

Referencing Table 3 further, there may also exist potential employees for STEM employers among the 4,452 disabled Americans with non-STEM degrees (BA+) working in non-STEM occupations. Here, the estimate could represent approximately 445,200 disabled Americans available as potential employees for STEM employers. Even if the job is not in a STEM field, the findings suggest disabled Americans would have a greater likelihood of higher wages employed in a job with a STEM employer than working in a non-STEM occupation. Even so, the table entry of 972 disabled Americans with a non-STEM degree (BA+) now working in a STEM occupation—representing 97,200 in the US population—provide another potential source for increasing professionals in STEM fields but would require a STEM employer to invest in their education, technical training, and opportunities for technical STEM-related work.

Lastly, opportunities exist for a STEM employer to hire disabled Americans below the Bachelor's degree, including those with cognitive disabilities, assuming the employer can provide appropriate accommodations and sustained supports to a disabled worker in the workplace (Bonaccio et al., 2020). Appropriate workplace accommodations can lead to more creative work by employees with disabilities by enhancing their creative self-efficacy and problem-solving skills (e.g., Man et al., 2020). More so, coping with everyday life challenges can also result in higher abilities to concentrate and deal with adversity. Yet, these talents and abilities can be quashed by the non-disabled population in the workplace because of their misunderstandings, a lack of inclusivity policies, and biases against people with disabilities (Noa & Akhtar, 2021).

Even so, individuals with disabilities face multiple barriers in the scientific workforce, including a lack of systemwide recruitment of individuals with disabilities, and workplaces have limited resources for staff training and purchasing accessibility-related technology (Bellman et al., 2018). STEM employers have options to increase Americans with disabilities in STEM occupations. For example, the EEOC provides the following non-exhaustive list of suggestions to end wage inequity and provide equal employment opportunities for all workers (Coleman et al., 2021).

- Offer bias training to all employees
- Establish mentoring programs
- Provide opportunities for meaningful work assignments
- Establish meaningful paths to advancement, such as pathway programs
- Provide necessary accommodations outright instead of as an afterthought
- Provide work flexibility, such as alternate work schedules and telework
- Add inclusive practices in performance ratings

- Demonstrate a commitment to equal employment throughout the organization
- Discipline workers found to discriminate against underserved employees

This being so, the current study recognizes the constraints but also the possibilities to what VR providers can recommend to employers to increase employment of disabled Americans in STEM occupations at equal pay comparable to their non-disabled peers.

4.3. Future research

Expanding the Mincer model in future research to include additional variables might illuminate further the context of wage disparities among Americans with disparities. Certainly, newer findings would add to the labor market literature, and to helping NCSES researchers better understand the employment of those with disabilities in STEM occupations (NCSES, 2021, p. 54). Other lines of research are more pragmatic. As cited earlier, the discrepancies in the wage multipliers suggest differences may exist in how well Americans with disabilities derive and use social capital to self-advocate in securing equal, competitive salaries compared to their non-disabled peers. As an analogy, if STEM education is the fulcrum upon which qualifying for a STEM job relies on, then social capital is the force on the lever that Americans with disabilities need to negotiate with employers for wages comparable to workers without disabilities employed in similar STEM occupations.

To explore this supposition, researchers could employ best practices in research designs to study social capital development and application (e.g., Demirkiran & Gencer, 2017; Seibert et al., 2001), but within the context of pursuing a STEM career (e.g., Dutta et al., 2015). Using purposeful sampling methods to identify workers with disabilities employed in STEM occupations making comparable wages as their non-disabled peers in similar jobs, researchers could use qualitative methods to learn how each group effectively used social capital for STEM career success. More so, how they developed their social capital would be paramount to this research. Such findings would provide VR providers, educators, counselors, and employers with ideas for social capital interventions that effectively prepare workers with disabilities to self-advocate and negotiate and thereby, secure equal, competitive salaries compared to their non-disabled peers. Having done so, this would broaden their participation in STEM careers.

5. Conclusions

There are three main insights derived from the current study. The findings suggested that opportunities exist for employers to hire qualified Americans with disabilities seeking gainful employment in STEM occupations. Identifying and recruiting such candidates into STEM jobs should therefore be paramount to employers seeking to diversify its workforce in technical fields. The findings also suggested that within the Americans with disabilities group, working in a STEM occupation with a college degree in a STEM field was the best route to attain maximum wages. Of course, one could earn higher wages to some extent by working more hours-per-week and weeks-per-year in the private industry where wages are greater than in the public or non-profit sector. Even so, advanced STEM degrees resulted in still higher wages, which aligns with many of the economic and personal benefits workers perceive when seeking an advanced STEM degree (Torres-Olave, 2019).

The third insight from the current study cannot be avoided: the noticeable gaps in wage multipliers between Americans with disabilities compared to Americans without disabilities. Future researchers should focus on the extent that these wage disparities were manifested by disabled workers' career and employment decisions within the context of social capital. Such research would inform VR providers on selecting interventions to bridge any knowledge and technical gaps through education and training and thereby, increase the likelihood of gainful employment for Americans with disabilities in STEM occupations comparable to their non-disabled peers. In so doing, it could significantly reduce any residual effects on wage disparities from unobserved characteristics in the STEM workplace that may be rooted in discrimination towards individuals with disabilities still lingering in American society and workplace.

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Conflict of interest

The author declares no conflict of interest.

Ethical declaration

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