The Impacts of Physical Disabilities on Labor Market Outcomes: A Tanzanian Case Study

by

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Abstract

This thesis explores the labor market impacts of physical disabilities in Tanzania using the 2010/2011 Tanzania National Panel Survey (TZNPS). Disability in a developing continent such as Africa needs to be studied in its own terms and environment. The impact of disability depends on the environment in which an individual is situated (Silversetein et al. 2005). Using probit regressions for employment, and log-linear regressions for earnings and also controlling for a range of personal characteristics, we find that disability is found to be an important determinant of employment and wage. We also detect differences in the regression slopes due to disabilities. We, thus, consider how model specification and econometric methods affect employment and wage differentials between disabled and non-disabled labor market participants. Oaxaca and Fairlie decomposition models are used to measure these intergroup gaps. This paper establishes a clear intergroup endowment gap, but it also finds an enormous unexplained gap. This unexplained gap alludes to the significant roles of employment and wage discrimination. Ensuring access to Secondary Level Education and promoting geographic mobility are some of the interventions this paper propounds to address the intergroup productivity and endowment differential.[1]

Introduction

On the basis of disability, we have observed clear differences in employment outcomes, earnings, and quality of life (Acemoglu and Angrist, 2001 and Deleire, 2000). Access to employment opportunities and income are two notable indicators of a person's quality of life. There is no single, consistently used, definition or method for classifying the disabled, and physical disability is only one form of disability. A school of thought posits that people are disabled when functional limitations impede on people's ability to perform activities necessary to maintain or improve their quality of life (instead of solely experiencing permanent or transitory physical or mental limitations). Explaining disability in terms of how functional limitations restrict the ability to perform activities provides the basis for this analytical work to be conducted.

The relevance of confronting disability for poverty reduction and development has long been neglected by development actors and only marginally addressed at the policy and implementation levels (Fritz et. al, 2009). The implementation of the UN Convention on the Rights of Persons with Disabilities (UNCRPD) on 3 May 2008 made disability, now framed as a human rights issue, an important part of the mainstream development agenda.

The subsequent section sets reviews the empirical evidence on the topic. This is followed by the section that establishes the econometric methods, the dataset for the analysis, and the variables in focus. Third comes the regression and decomposition sections, exploring employment first and earnings next. We conclude with a rehash and discussion of the outcomes alongside the literature, and point out areas of possible policy intervention.

Empirical Evidence

Though disability exists in a continuum, societies around the world interact with disability largely through several layers of dichotomized frameworks. The society tends to see people as either disabled or not, and the ramification of this dichotomy is pervasive in the labor market where the impression of people's productivity tends to also be translated into a dichotomy. This dichotomized view of disability is also present in the way we study disability. Most of the rigorous empirical studies on how physical disabilities affect labor market outcomes have focused on high-income countries, whereas majority of the world's disabled live in the developing world. Disabilities could also be viewed from the prism of rural vs. urban. A World Bank disabilities and poverty survey found that there are higher proportions of people with disabilities in rural (and poorer) areas (Bickenbach, J., 2011).

Literatures show that employment, wage are affected by one's education (Huang, 1999), gender (Oaxaca, 1973), disabilities, experience, and urban/rural (Phimster, 2005). The human capital framework provides an explanation for the labor market wage and employment differentials, which is underscored by the assumption that there is a significant productivity gap beyond disabled and non-disabled. It predicts that the least educated workers, who by presumption possess fewer formally developed skills of cognitive and technical adaptability, tend to experience the greatest disability induced reduction in wages.

Taste based discrimination (Becker 1971), which is underpinned by prejudice, and statistical discrimination are the dichotomized frameworks for understanding discrimination in the labor market. Statistical discrimination, in essence, results when the actual or assumed statistical properties of a group are applied to anyone belonging to that group. Contrary to the above more traditional explanation of statistical discrimination, it has been posited that statistical discrimination could come about as result of factors beyond the average outcomes of one's group. These factors include noisier productivity signals (Aigner & Cain, 1977), differential screening or communication costs (Cornell and Welch 1996; Lang 1986).

Studies consistently identify employment effect of disability. The presence of wage discrimination forces some individuals to exit the labor market (Baldwin and Johnson, 1994), and explain some of the observed differences in employment rates. This disincentive effects of wage discrimination account for only two of the twenty-nine-percentage points and less than one percentage point, of the 26% gap in employment rate for disabled men and disabled women respectively (Baldwin and Johnson, 1994 & 1995). Disabilities affect the type of employment undertaken. Disabled people are twice as likely to be self-employed (Blanck et al., 2000).

There are two main explanations as to why people with disability are more likely to be self-employed. Firstly, employer discrimination reduces the relative wages of disabled employees, making self-employment more attractive. Secondly, the disabled may gain greater freedom and flexibility to accommodate their disability through self-employment. Evidence suggests that flexibility is a dominant reason, and that these forms of employment enable individuals who are unable to undertake in standard types of employment to work (Jones, 2008). Flexibility turns out to be a social amenity that comes with a cost. Not only are disabled people more likely to be self-employed, they are concentrated in non-standard forms of employment that have lower wages and fewer benefits on average (Schur, 2003). Even after controlling for personal characteristics, disabled people are significantly more likely to be in temporary and part-time employment.

Approximately 10% of the observed wage differential for men, and 20% for women, are potentially attributed to discrimination - with job demands and interactions included in the wage model (Baldwin & Chung, 2014). Studies that have sought to decompose the gap in employment probabilities find that about half of the difference in employment probability is explained by the differences in characteristics (Kidd et. al., 2000). This increases to over 70% when productivity and selection issues are controlled for (Madden, 2004).

The growing understanding of disabilities as a global phenomenon is compromised by the scarcity of quality research with focusing on the developing regions. The impact of disability depends on the environment in which an individual is situated (Silversetein et al. 2005). The power of a wider drawn geographical conclusions from an econometric finding become more substantial with external validation. This paper investigates the labor market outcomes of disability in the East African country of Tanzania.

Data and Econometric Methods

Characteristic of the Study Participants

This thesis uses the 2010/2011 Tanzania National Panel Survey (TZNPS), a cross-sectional dataset that was conducted as part of the LSMS Integrated Surveys on Agriculture project.[2] There are 16,000 individuals, in 3,280 households in this TZNPS program. The exclusion criteria for this project which comprises of those aged below 17 and those aged above 65, and individuals who are missing key demographic variables. This produces a sample of people in their prime working age. The ultimate dataset comprises of 4,739 individuals (about 300 are classified as disabled).

Employment & Earnings

This econometric methodology is in line with previous analysis of the impact of disability on employment and earnings (Kidd et al. 2000, Madden, 2004 and Jones, 2008). We use the probit regression technique for employment.

Binomial Equation for the probit regression is represented:[3]

$$\Phi(\mathcal{Z}) = P_i = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{z_i} e^{-s^2/2}\, ds \qquad (1)$$

Where:

P_i = the probability that the indicator variable D_i = 1

$$\text{Employed}_i = \Phi^{-1}(p) = \mathcal{B}_0 + \mathcal{B}_1 Disability_i + \mathcal{B}_2 Rural_i + \mathcal{B}_3 Gender_i + \mathcal{B}_{04} Education_i + \mathcal{B}_5 Marital\ Status_i + \mathcal{B}_6 Region_{1i}$$

s = a standardized normal variable

The derivative of the equation shows the marginal effect of one-unit change in x on the probability that *y* = 1.

We modify the Mincerian wage (Mincer, 1974) regression specification by including a disability dummy:

$$\ln\big(w(s, x, disability, region)\big) = a_0 + \rho_s.S + B_0.X + B_1.X^2 + B_1.Disability + B_1.region\ldots \qquad (2)$$

Decomposition

We use the Blinder-Oaxaca model to decompose earnings. The Blinder-Oaxaca decomposition technique quantifies the separate contributions of group differences in measurable characteristics (Blinder (1973) and Oaxaca (1973)). This technique only requires coefficient estimates from linear regressions for the outcome of interest and sample means of the independent variables used in the regressions. With only two x's - x_1 and x_2, we write the following equation:

$$\boldsymbol{lny^{nondisabled} - lny^{disabled}} \qquad (3)$$

$$= \left(\beta_0{}^{nondis} - \beta_0{}^{dis}\right) + \left(\beta_1^{nondis} x_1^{nondis} - \beta_1^{dis} x_1^{dis}\right) + \left(\beta_2^{nondis} x_2^{nondis} - \beta_2^{dis} x_2^{dis}\right)$$

$$= \mathbf{G0} + \mathbf{G1} + \mathbf{G2}$$

Distinguishing between the proportion of the difference that is due to (i) differences in the x's (sometimes called the explained component) rather than (ii) differences in the β's (sometimes called the unexplained component), can be represented with the equation below:

$$\boldsymbol{y}^{\boldsymbol{nondis}} - \boldsymbol{y}^{\boldsymbol{dis}} = \left(\Delta x \beta^{dis} + \Delta\beta x^{nondis}\right) \tag{4}$$

where:

$$\Delta x = x^{nondis} - x^{dis} \text{ } and \text{ } \Delta\beta = \beta^{nondisabled} - \beta^{dis}$$

Note: dis is disabled and nondis is nondisabled

To decompose employment, we use the Fairlie (1999) model of decomposing indicator variables which use logit or probit models. This is because the Blinder-Oaxaca decomposition technique is not devised for binary outcomes (i.e. is one employed or not).

$$\overline{Y}^W - \overline{Y}^B = \left[\sum_{i=1}^{N^W} \frac{F(X_i^W \hat{\beta}^B)}{N^W} - \sum_{i=1}^{N^B} \frac{F(X_i^B \hat{\beta}^B)}{N^B}\right] + \left[\sum_{i=1}^{N^W} \frac{F(X_i^W \hat{\beta}^W)}{N^W} - \sum_{i=1}^{N^W} \frac{F(X_i^W \hat{\beta}^B)}{N^W}\right], \tag{5}$$

The first term in bracket represents the part of employment participation (work) that is due to group differences in distributions of X, and the second term represents the part due to differences in the group processes determining levels of Y. The second term captures the portion of the work gap that is due to group difference in unmeasurable or unobserved endowments (Fairlie, 2005). Note: endowments terms are the contributions of differences in the explanatory variables across groups; coefficient terms could be said to answer the question, “how different are the groups?”

Deriving the Relevant Variables

A. Constructing Indicators for Physical Disabilities (IFAL & Self-Reported measures)

The Self-Reported Disability Measure and Individual’s Functional Activities Limitation (IFAL)[4] are two of the most popular measures of disabilities. Some literatures have raised questions on the validity and accuracy of the Self-Reported measure because of the perceived subjectivity in the responses (Kreider and Pepper (2007)). On the contrary, Stern (1989) finds that a self-reported disability question is close to exogenous. To the extent self-reported disability was endogenous, the relationship was the opposite of what had been hypothesized in the literature (i.e. health tended to deteriorate when working rather than disability being used to justify not working).

Individual’s Functional Activities Limitation (IFAL) measure of disability is considered to be more objective (Bound, 2001). The IFAL measure may also suffer from some of the same shortcomings as the Self-Reported measure. The IFAL measure still relies on the individual’s perception of their ability to carry out the specific motor functions in the questionnaire. However, the very fact that many of these physical disabilities can instantly be observed by the survey agents, could be considered a validity check of sort on the information provided. This paper adopts IFAL as the measure of disabilities of choice after conducting additional stress tests.[5] The Self-Reported measure ultimately serves a supplementary role.

B. Labor Market Demographic Characteristics and Controls

Employment & Earning are the two dependent variables. The control demographic factors with respect to the employment analysis are *physical disabilities*, *gender*, *educational attainment*, *urban/rural status, age, marital status, and region.*[6] With respect to the *earnings analysis*, the control demographic factors include largely the same variables as the *employment analysis*.[7]

Table 1(a): Tabulation Statistics of Urban & Rural Dwellers by Occupation Type

	Rural Dwellers		**Urban Dwellers**	
	General	**Disabled**	**General**	**Disabled**
Occupation Type	Frequency	Frequency	Frequency	Frequency
Self-Employed - Farming	3,650 (81.5%)	163 (76.5%)	358 (12.5%)	22 (12.6%_
Self-Employment – Other	212 (4.7%)	7 (3.3%)	799 (27.8%)	58 (33.1%)
Wage Employed - Private	102 (2.3%)	4 (1.9%)	453 (15.8%)	12 (6.9%)
Wage Employed - Non-private	122 (2.7%)	2 (0.9%)	242 (8.4%)	10 (5.7%)
Unemployed/not active	391 (8.7%)	37 (17.4%)	1,022 (35.6%)	73 (42%)
Total	**4,477**	**213**	**2,874**	**175**

Table 1(b): Tabulation Statistics of Educational Attainment

Education (Indicators)	IFAL == 1	IFAL == 0
	Frequency	Frequency
No Education	86 (31.6%)	926 (20.7%)
Completed Less than Grade 7	74 (27.2%)	74 (27.2%)
Grade 7 to Form 4 Completed	107 (39.3%)	2715 (60.8%)
Completed Ordinary Levels	5 (1.8%)	183 (4.1%)

NB: IFAL == 0 means non-disabled by the IFAL measure, and IFAL == 1 means disabled by the same measure. Same idea goes for self-employed.

Dependent Variables for Employment

"Worked for Wage" variable is strictly determined on whether or not the participant worked for some monetary remuneration in the last 12 months. "Worked All Condition" variable loosens the monetary remuneration requirement. "Worked for Wage" variable is the principal variable of this analysis, and "Worked All Condition" plays a supplemental role.

Dependent Variables for Earnings (Wage)

Earnings are the dependent variable used to estimate income in this section of the analysis. The means and frequency of these monetary remunerations are diverse. We constructs a standardized earnings variable by using a consistent time conversion metrics (hourly wages).

Estimations and Results (Employment)

We run a binomial probit estimations for employment, controlling for the relevant factors. We show how physical disabilities, differently, influence the demographic characteristics in our regressions by interacting physical disabilities with the control variables and finding the joint F-statistics. The disabilities indicators show a different regression slope for disabled people. We subsequently use Fairlie's decomposition technique to examine this intragroup employment gap.

Regressions Results: Employment and Physical Disabilities

To assess the labor market participation for the disabled and non-disabled groups, we use the probit model - a non-linear maximum likelihood estimation. The derivative of this probit model equation shows the marginal effect of one-unit change in x on the probability that y = 1. Table 2 shows the results of the Binomial Probit regressions from equation 1.

Table 2: Binomial Probit Model for Employment

VARIABLES	Worked All Conditions	Worked All Conditions	Worked for Wage	Worked for Wage	Worked for Wage (Interaction Effect)	Worked for Wage (Interaction Effect)
IFAL	-0.0532*** (0.0149)		-0.186*** (0.0347)		-1.817 (1.457)	
Self-Reported Disability		-0.0642*** (0.0191)		-0.156*** (-0.038)		-0.0386 (2.075)
Constant			0.453*** (-0.0629)	0.501*** (-0.0688)	0.436* (0.337)	0.900*** (0.195)
Observations	4,447	4,449	4,739	4,741	4,737	4,730
F statistics[8]					Chi2 (22) = 44.86 Prob > Chi2 = 0.0028	Chi2 (23) = 33.98 Prob > Chi2 = 0.0655
R Squared	0.29	0.29	0.31	0.33	--	--

Notes: (1) Standard errors in parentheses below contribution estimates: *** p<0.01, ** p<0.05, * p<0.1.

Analysis of the Regression Results

The IFAL measure of disability classification reduces one's likelihood of "working for wage" by about 19 percentage points. When the wage requirement is removed resulting in "worked all condition", IFAL's effect on work goes down – a reduction of about 5 percentage points.

Market (economic) production and home production have traditionally been gendered systems. We find a one percentage point gender difference based on the work for wage requirement is significant but not enormous. The work for wage requirement may be excluding the large number of women who are in the informal economy/ home production. Wage usually means more empowerment so it is a factor that is worth some consideration.

Interactions: Determining the Slopes of the Disabled Group

We assess for any differences in slope between the disabled and non-disabled groups by interacting the demographic characteristics (controls) in our regression specifications with the disabilities measure(s), and subsequently conducting a joint F-test.

The coefficient of the regression with interactions should not be interpreted directly as the regression is non-linear. Unlike in linear models, the marginal effect of a change in the interacted variables is not equal to the marginal effect of changing just the interaction term.[9] This regression remains useful for implementing the F-test. It is the springboard for determining whether the slopes of the equations are different between disabled people and non-disabled people.

The F-test shows the slope is statistically significant. Irrespective of the measure of disabilities, physical disabilities convincingly change the slopes of the functional form for disabled people when worked is defined as 'worked for wage'. It is useful to decompose and investigate the causes of this slope differential, which manifests as asymmetrical access to paid employment.

Decomposing the Difference in Employment (Fairlie's Decomposition)

Of particular interest in this decomposition is whether (and how much) group differences in characteristics contribute to the difference in employment between disabled and non-disabled people. *Table 3* reports estimates of the Non-Linear Decompositions of Non-Disabled/Disabled Gaps in "Worked for Wage" using various coefficient estimates.

Table 3: Decompositions of Non-Disabled/Disabled (IFAL) Gaps in "Worked for Wage"

Specifications for Worked for Wage with IFAL		
	(1)	(2)
Sample used for coefficients	**Disabled/ Non-Disabled Pooled**	**Non-Disabled**
Non-disabled paid employment	**0.79**	**0.789**
Disabled paid employment	0.61	0.607
Disabled/Non-Disabled gap	0.18	0.183
Contributions from differences:		
	0.0123***	0.0123***
	(0.00157)	(0.00157)
Male	**6.8%**	**6.7%**
	-0.005*	-0.0064*
	(0.00335)	(0.00337)
Education	**-2.8%**	**-3.4%**
	0.031***	0.030***
	(0.00204)	(0.0022)
Rural	**17.2%**	**16.4%**
	-0.013**	-0.0213**
	(0.0068)	(0.0072)
Age	**-7.2%**	**-11.6%**
	-0.0017	-0.00071
	(0.003)	(0.0032)
MS	**-0.94%**	**-0.4**
	0.01143**	0.01148**
	(0.00274)	(0.0028)
Region	**6.35%**	**6.3%**
	0.035	0.026
All included variable	**19.1%**	**14.2%**
Observations	4,739	4,739

Notes: (1) SE in parentheses below contribution estimates: *** p<0.01, ** p<0.05, * p<0.1. (2) Contribution estimates are mean values of the decomposition using 1000 subsample of non-disabled

We conduct probit regressions using the two separate samples, 'Non-disabled' only and 'Disabled and Non-disabled' pooled. The individual contribution from gender, age, education, region and marital status are reported. The contribution for a set of dummy variables, such as those for region, is calculated by simultaneously switching distributions of all dummy variables. The results are generally similar across specifications. The difference in paid employment ("Work for wage") between the disabled and the non-disabled is about 0.18. As could be anticipated, the largest factor explaining this large disparity in paid employment is rural dwelling. Being rural and disabled account for ~17% of the disabled/non-disabled gap in the probability of paid employment ("Work for wage"). It seems paid work is less accessible for rural dwellers (see Table 1).

The differences in regions (Table 3) also contributes to the widening of the paid employment gap by about 6.3%. Enabling geographical mobility should be a focus of policy initiatives. The productivity of the disabled population would be improved by encouraging and reducing the barriers to intra-national migration. Furthermore, an intransigent gendering of the work is problematic. Stereotypically male professions are more likely to require movement and strength. Male and disabled contributes to the widening of the gap by about 6.75%.

Education and age among people with disability are two factors that contribute in the closing of the paid employment gap. Age and educational characteristics could be considered reasonable proxies for skills and experience. The data also shows that unemployment is most intractable among the least education percentile, policy intervention should target individuals with lower level of education and skills in general, and those with disabilities in particular.

Our decomposition reveals that group differences in all of the included characteristics explain less than 20% of the gap in paid employment ("Worked for wage"). Some of the gap could be a result of other unobserved characteristics that correlate with employment, examples include type and severity of disability. However, as evidenced by the literature and the magnitude of the unexplained difference, discrimination plays a significant role. Kidd et. al (2000) conclude that only about half the difference in employment is explained by differences in characteristics.

Estimations and Results (Earnings)

Regressing with earnings as the dependent variable begins with the transformation of the data to a log-linear multiple regression,[10] after which the process becomes similar to the employment regression. We also assess if physical disabilities differently influence the regression's characteristics (the slope) by interacting the variable for physical disabilities with the controls and implementing the joint F-statistics. If differences in slopes are observed, decompose using the Oaxaca-Blinder decomposition technique.

Log-Linear Multiple Regression Specification

Log-linear models are typically used to model relationships that are assumed to grow exponential. Wage estimation, for example, traditionally fits the exponential growth pattern (Mincer, 1974). Table 4 shows that at the lower end of the estimation disabled people earn about 40 percentage points less.

Table 4: Binomial Probit Model for Earnings

VARIABLES	Wage	Wage	Wage (Interaction Included)	Wage (Interaction Included)
IFAL	-0.386*** (0.135)		3.679* (2.123)	
Self-Reported Disability		-0.523*** (0.137)		3.347 (2.500)
Constant	3.881*** (0.377)	3.806*** (0.376)	3.693*** (0.387)	3.726*** (0.382)
Observations	2,158		2,158	
F-test for (Regions)	F(10, 2135) = 4.46 Prob > F = 0.0000	F (10, 2135) = 4.34 Prob > F = 0.0000		
Joint F statistics			F (18, 2117) = 1.35 Prob > F = 0.14	F (20, 2115) = 1.117 Prob > F = 0.2722
R-Squared	0.188	0.190	0.197	0.199

Notes: (1) Standard errors in parentheses below contribution estimates: *** p<0.01, ** p<0.05, * p<0.1.

Interactions: Determining the Slopes of the Disabled Demography

Table 4 also shows the outcomes of the interactions & the subsequent F-test. As earlier stated in the slope determination discussion, the above regression is non-linear. The ultimate use of the marginal effect regression table is the ability to determine the inter-group slopes using the F-test. With an F value of 0.14, the null-hypothesis is rejected (for IFAL disability measure) at a 0.15 significant level.[11] With regards to earnings, physical disabilities (as measured by IFAL) change the slopes of the equation’s functional form. We thus go ahead to decompose and investigate the causes of this differential in slope for IFAL.

Oaxaca-Binder Decomposition

Oaxaca-Binder technique decomposes wage differentials into two, one part that is explained by two groups having different productivity characteristics, and the other that is unexplained and very likely because of the preferential treatment of one group over the other. The former is the characteristics effects and the latter is called the coefficient effect.

For our earnings specification, we compute the Oaxaca-Binder technique below.

Table 5 (a): First Block of Output from decompose (IFAL Measure)

Mean prediction Non-Disabled (H):	4.919
Mean prediction Disabled (L):	4.415
Raw differential (R) {H – L}:	0.504
- Due to endowments (E):	0.209
- Due to coefficients (C):	0.383
- Due to interaction (CE):	-0.088
First block: The mean value of earnings for the disabled and non-disabled groups.	

Table 5(b): Second Block of Decomposition (IFAL Measure)

D:	0
Unexplained (U){C +(1-D)CE}:	0.295
Explained (V) {E+D*CE}:	0.209
% unexplained {U/R}:	58.5
% explained (V/R):	41.5
The second block: This table shows the explained and unexplained portions of the outcome gap	

Table 5 (a) reports the mean values of log earnings for the disabled and non-disabled. The difference between these two groups is 0.504. The contribution attributable to the gaps in endowments (E) is 0.209; 0.383 is attributable to the coefficients (C), and the interaction (CE) is -0.088. Endowments reflect the mean increase in the disabled's earning if they had the same characteristics (mostly productivity related) as the non-disabled. The increase of 0.209 indicates that the difference in endowment accounts for about 40% of the earnings gap. Coefficients quantify the change in the disabled's wage when applying the non-disabled's coefficients to the disabled.

From the Oaxaco-Binder equation establish Table 5 (b), i.e. the explained and unexplained parts, by making D = 0. Note that the interaction effect is also a part of the unexplained. Table 5(b) shows that about 60 percentage points of the difference between disabled and non-disabled is unexplained, which is more than the portion that is explained by differences in endowment (~40%).

Table 5(c): Third Block of Output from decomposition

	Explained: D =	
	IFAL Measure of Disabilities	
Variables	E (D=0)	CE
Age	1.135	-1.865
Age Squared	-1.164	1.884
Male	0.086	0.015
No Education Attained	0.073	0.015
Less than D7 Education Completed	0.09	0.026
D7 to F4 Education Completed	-0.049	-0.075
Rural	-0.046	0.035
Occupation Type 2	0.012	-0.02
Occupation Type 3	0.035	-0.038
Occupation Type 4	0.042	-0.016
Regions (Merged)	-0.05	0.214
Constant	0.00	0.000
Total	0.209	-0.088

The third block of output table 5(c) shows the extent gaps in individual x's (the controls) contribute to the overall explained gap. Equate D to 0 and to the interaction term.

Secondary level education serves to bridge the earnings gap, while educational attainment below the secondary level widens the gap. This phenomenon could be interpreted from the skilled vs. unskilled framework. Disabled labor market participants are even more at a disadvantage when their human capital is applied to unskilled and more manual type of jobs. From the tabulation statistics of educational attainment (Table 1b), it observes that the attainment of some secondary level education for with disability (39%) lags that of their non-disabled counterparts (61%).

This analysis proves out that there is indeed an endowment difference between the disabled and non-disabled, but that theirs is an even wider unexplained inter-group gap. Closing this endowment gap would increase earnings for the disabled by about 40%. An unexplained difference of this magnitude makes discrimination a significantly more probable factor. Our results also brings the human capital framework back into focus; the framework predicts that the least educated workers, who by presumption possess fewer formally developed skills, will tend to experience the greatest disability induced reduction in wages.

Conclusion

Our plan from the outset has been to establish that the Tanzanian labor market participants with physical disabilities experience a worse employment and earnings outcomes, and to investigate the reason this is the case. Given that literature asserts that the impact of disability depends on the environment in which an individual is situated (Silversetein et al. 2005), this paper takes the route of investigating this question in a less studied region of the world. The data for this analysis are from the 2010/2011 Tanzania National Panel Survey (TZNPS), a cross-sectional survey dataset collated as part of the Living Standard Measurement Survey (LSMS) Integrated Surveys on Agriculture project.

The following demographic factors are the controls used for these regressions: gender, education, urban/rural status, age, marital status, and region, and occupational/industry type. The use of these controls are grounded in the findings of past studies. In the regression analysis with employment as the dependent variable, all the controls above except "occupation/industry types" are included. In the regression analysis with earning as the dependent variable, all the controls but marital status are used.

We explore these different components of the question with different econometric tools: probit regressions for employment and log-linear regressions for earnings, and consequently test for inter-group difference in slope using the F-test. Given an inter-group difference in slope, which shows that in terms of earnings and employment, the labor market treats people with disability differently, we investigate by decomposing. The Oaxaca-Binder and Fairlie models of decompositions account and explain these earnings and employment gaps.

Employment, Earnings and the role of discrimination

Being disabled reduces the likelihood of working by ~20 percentage points, while reducing the log of earnings by ~40 percentage points. Proving discrimination is usually a more difficult proposition. The assessments of the slopes of the specifications, using the F-test, demonstrates that in terms of employment and earnings, the labor market treats the physically disabled differently.

The statistical significance of this difference in slope is more robust for employment than for earnings. The higher the unexplained portion of the decomposition, the higher the probability of discrimination being a significant factor. Decomposition of the intergroup difference in earnings shows a raw difference of 50%, of which only about 40% is explained by the differences in endowment. For the paid employment analysis, the raw difference is about 20 percentage points, of which about 80% remains unexplained.

Comparing the explained and unexplained portions of earnings and paid employment, this paper concludes that paid employment has a higher probability of what seems to be discrimination induced barrier. Putting differently, our analysis finds that the labor market treats people with disabilities differently in terms of both employment and earnings, with the difference in employment being more significant. After subsequently decomposing, we find that employment also has a higher proportion of this gap unexplained that has been attributed to discrimination. Literature reaffirm these findings. Baldwin & Chung (2014), and Kidd et al. (2000) posit that while the wage gap is a critical issue, the differences in employment probabilities facing people with disabilities is even more dramatic.

Our findings also reaffirm the human capital framework; the framework predicts that the least educated workers, who by presumption possess fewer formally developed skills, will tend to experience the greatest disability induced reduction in wages. Some secondary level education reduces both the earning & employment gaps.

We find some noteworthy sample statistics that put the aforementioned decomposition in context. The inter-group divergence in secondary level education is significant: 39% of those with disabilities get some secondary education, while the rate is 61% in the non-disabled group. The suggestion in the literature that people with disability tend to be more self-employed (given the flexibility of self-employment) is supported by the sample statistics of the dataset. In urban areas where farming is impractical, the rate of non-farm self-employment among people with disability is 33% while it's only 28% in that general population.

The Roles of Discrimination

Prior studies posit that more than half of offer wage & employment differential between disabled and non-disabled women is attributable to discrimination ((Baldwin and Johnson, 1994 & 1995) and (Kidd et. al., 2000)). It has been argued that this portion increases to 70% for the employment differential when productivity and selection issues are controlled for (Madden, 2004). It is impractical to incorporate all the necessary controls and explanatory variables is impractical due to data and econometric limitation. This challenge stands in the way of making even more definite assertion of the role of discrimination in shaping labor market outcomes.

Nevertheless, this paper finds an unexplained gap of 80% (of the 20-percentage point gap in employment) and 60% (of the 50-percentage point gap in earning) makes the assertion that discrimination plays a significant role seem like a foregone conclusion. As mentioned earlier, our decomposition analysis shows that access to paid employment has a higher probability of discrimination induced barrier compared to earnings. Metaphorically speaking, getting a leg in the door would ameliorate the labor market challenges of people with disabilities.

Recommendations

Taking a leaf from the human capital framework could help ameliorate some challenges. Policy initiatives should be targeted toward improving access to secondary level education and skills, especially for those with disabilities. With the right level of human capital development, one could more effectively choose between seeking out a paid employment, or doubling down on the work flexibility that self-employment offers. Given that the impact on discrimination is significantly more for employment than for on earnings, initiatives to improve access to employment for people with disabilities e.g. job matching services should be explored.

The data decomposition shows that the type of roles male with disabilities take contribute to this labor market gap. The gendering of jobs seems problematic in this light. Traditional male professions are more likely to require movement and strength, and this is a detriment for physically disabled people. The regional asymmetry of productivity among people with disabilities provides room for intervention. The welfare of these populations would be enhanced by migrating to regions where their productivity is higher. Policies that enable intra-national geographical mobility as a way of boosting productivity should also be explored.

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Notes

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[1] Prof. Denise Hare of the Department of Economics at Reed College advised this paper.

[2] NPS is a nationally representative household survey on the living standards of the population. For more information - " Worldbank.org, Site Tools." LSMS - Living Standard Measurement Survey.

[3] The probit function is the inverse of the cumulative distribution function of the standard normal distribution, which is denoted as $\Phi(z)$, so the probit is denoted as $\Phi^{-1}(\mathcal{P})$. This integral expression is the probability that a standard normal random variable fall to the left of point z.

[4] IFAL disability measure is derived through a checklist of core physical locomotive functions.

[5] People's employment situation in one year could influence their decisions to call themselves disabled in that particular year or the next (reverse causality). A look at how the physical disabilities indicators in one TZNPS survey year differ from the previous survey year shows no change in responses for the individuals in the sample.

[6] The categories for Education - “Grade 7 to Form 4 Completed”, “Completed Ordinary Levels”, “Completed Less than Grade 7” & “No Education.” For Occupation Type - Occupation Type 1: self-employed (farming); Occupation Type 2: self-employed (non-farm); Occupation Type 3: private sector paid work (e.g. mining); Occupation Type 4: non-private sectors work (e.g. government agencies and religious organizations); Occupation Type 5: unemployed or not active (e.g. unpaid workers and job seekers). For Marital Status - “Widowed”, “Monogamous”, “Polygamous”, “Living Together”, “Separated”, & “Divorced.”

[7] The Earnings analysis excludes the control for marital status while including controls for occupational type.

[8] Joint F-statistics for assessing the specification slope.

[9] In non-linear models, interaction effects are conditional on all explanatory variables (Norton et. al.,2004). As a result, the interaction effect could be non-zero, even if $\beta12 = 0$; the statistical significance of the interaction effect cannot be tested with a simple t test on the coefficient of the interaction term $\beta12$; the interaction effect is conditional on the independent variables; the interaction effect may have different signs for different values of covariates (Frondel and Vance, 2012).

[10] Testing our model for heteroskedasticity using the Breusch-Godfrey test, we ensure the robustness of the errors. Stock and Watson (2007) conclude that regression errors in estimating log (wage) are robust.

[11] Proving the existence of a difference in slope between groups especially with regards to discrimination is not a simple task, hence a significant level of 0.15 is considered more realistic and less prone to Type I error.