Employment and Education Discrimination against Disabled Persons in Cape Verde

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Abstract

This paper assesses the employment and school enrollment gaps between disabled and non-disabled persons using the last Cape Verdean census. The unexplained part of these gaps accounts for most of them, whatever the age group considered. Furthermore, differences in age structures between disabled and non-disabled persons have almost no effect on these gaps. Taking into account potential misclassification errors in the disability variable seems to change only marginally these results. These findings thus suggest that there is scope for programs to better target and promote employment and education of the disabled in Cape Verde.

Keywords: disability; economic and social discrimination; misclassification; Cape Verde; Africa.
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1 Introduction

Disability is a major concern for policy makers when the focus is brought to bear on reducing vulnerability and extreme poverty in developing countries. Disabled persons may indeed be those most affected by lower incomes, lower perspectives on the labor market and lesser access to education. The World Health Organization defines a disabled person as being a person whose physical and mental integrity is temporarily or definitely diminished, either because of age or illness, so that his/her autonomy, his/her aptitude to go to school or get a job is compromised.

In order to examine discrimination between disabled and non-disabled persons in developing countries, this paper assesses the employment and school enrollment gaps between these groups, using data from the 2000 Cape Verde census. These data are of particular interest as they are exhaustive. The information available in this census allows us to conduct a variety of cross-variable studies, even though the proportion of disabled persons may be very small. Comparing various categories of people (across age, gender, etc.) is simpler than with surveys: indeed, with this exhaustive census sample, statistics are accurate, while analyzing disability from a general household survey is less reliable. What is more, censuses are available at regular intervals as well as in numerous countries, so that it is possible to make temporal comparisons as well as cross-country comparisons. Censuses may also be used to analyze geographic disparities of disability at a very detailed level. However, due to self-declaration, disability variables in censuses (as in surveys) can be concerned by measurement error. Furthermore, census questionnaires are rather small, so that it can be difficult to analyze certain complex situations.

In West African countries, about 1-3% of the population has a declared disability in census data, while an estimated 10% of the world's population experiences some form of disability. One key explanation for the low disability rates in Western African countries is that not all forms of chronic diseases are reported in census data. Moreover, international comparisons based on self-reported disability status find important variations between countries even if identical questions are asked (Banks et al., 2004). Misclassification may indeed be an important source of differences between self-assessed disability rates, and should be taken into account for our purposes.

The methodology used to assess the presence of disability-based discrimination in the labor market or at school relies on a suitable decomposition technique. First, Oaxaca-Blinder type decomposition has been adapted to binary variables by Fairlie (1999, 2005) so that it can be used in order to analyze the employment and school enrollment gaps between disabled and non-disabled persons.[1] Second, we decompose these gaps across age groups so that we can assess the part of these differentials that is due to differences in age structures between the disabled and the non-disabled. Third, we further assess the sensitivity of these decompositions to misclassification error of the binary disability variable using the modified maximum likelihood approach proposed by Hausman et al. (1998).

Our findings show that the employment and education gaps in Cape Verde are mainly unexplained by observed characteristics differentials. Differences in age structures between disabled and non-disabled persons do not explain much of these gaps either. These differentials should thus be due to discrimination or differences in unobserved characteristics. We also observe that the employment gap increases with age. In rural areas, employment discrimination between disabled and non-disabled persons is perceptible from the earliest stages of employability. Regarding education, the disabled are discriminated against starting in elementary school. What is more, these findings are robust to misclassification errors.

One interesting consequence of these findings is that disability has a cumulative impact on education and then on employment; discrimination thus reinforces over the life cycle, so that disability-oriented policies should be aimed at reducing discrimination at a younger age in order to overcome persistent inequality. This interpretation of our findings should however be further assessed using other data in order to isolate unobserved heterogeneity determinant of employment and education differentials.

This paper is organized as follows. The second section presents the methodology of decomposition of the school enrollment and employment differentials. The third section presents Cape Verdean census data. Empirical results are provided in the fourth section. The last section concludes.

[1] See also an application of this method to disability discrimination in India by Mitra and Sambamoorthi (2008).

2 Decomposing Employment and School Enrollment Differentials

Non-linear decomposition techniques proposed by Fairlie (1999, 2005) or more recently by Yun (2004) and Bauer and Sinning (2008) allow us to adapt Blinder-Oaxaca type decomposition to binary dependent variables such as employment and school attendance variables. Defining $Y = F(X\beta)$ where X is a vector containing independent variables such as observed individual and household characteristics, we can write:

$$\bar{Y}^{ND} - \bar{Y}^{D} = [\overline{F(X_{ND}\beta_{ND})} - \overline{F(X_{D}\beta_{ND})}] + [\overline{F(X_{ND}\beta_{ND})} - \overline{F(X_{ND}\beta_{D})}], \quad (1)$$

where subscripts and superscripts D and ND respectively indicate disability and non disability. The overbar means that we average over the sample population. The first term on the right hand side of the equation is the part of the employment gap or the school attendance gap explained by differences in observed characteristics, whereas the second term is the part attributable to differences in returns to these characteristics. The latter term also represents discrimination. In equation (1), the first term is based on estimates of what a disabled person would experience if he/she were not disabled. Alternatively, we can write:

$$\bar{Y}^{ND} - \bar{Y}^{D} = [\overline{F(X_{ND}\beta_{D})} - \overline{F(X_{D}\beta_{D})}] + [\overline{F(X_{ND}\beta_{ND})} - \overline{F(X_{ND}\beta_{D})}]. \quad (2)$$

Unfortunately, the two expressions generally do not give the same results. As proposed by Neumark (1988), this well-known index number problem can be resolved by using a pooled regression to estimate the coefficient β that can be used in the expression. The new decomposition is:

$$\begin{aligned} \bar{Y}^{ND} - \bar{Y}^{D} = \; & [\overline{F(X_{ND}\beta)} - \overline{F(X_{D}\beta)}] + [\overline{F(X_{ND}\beta_{ND})} - \overline{F(X_{ND}\beta)}] \\ & + [\overline{F(X_{D}\beta)} - \overline{F(X_{D}\beta_{D})}], \end{aligned} \quad (3)$$

where the first term represents the proportion of the gap explained by observed characteristics, while the two other terms represent the contribution of the returns to observed characteristics.

A further decomposition should be applied by differentiating across age groups. Indeed, there can be differences in employment and school attendance determination across age groups, since disability stigma may change over the life cycle.

For instance, there may be living arrangements between older persons and their families, whereas unemployment may be experienced as a social stigma among younger persons. Noting K the number of age groups, we decompose the employment gap and the school attendance gap as follows:

$$\bar{Y}^{ND}-\bar{Y}^{D}=\sum_{j=1}^{K}\bar{p}_j(\bar{Y}_j^{ND}-\bar{Y}_j^{D})+\sum_{j=1}^{K}\bar{Y}_j^{ND}(\bar{p}_{NDj}-\bar{p}_j)+\sum_{j=1}^{K}\bar{Y}_j^{D}(\bar{p}_j-\bar{p}_{Dj}), \quad (4)$$

where $\bar{p}_{NDj}$ and $\bar{p}_{Dj}$ are the sample proportions of non-disabled and disabled persons in age group j. By considering $\bar{p}_j$ the sample proportion of the whole population in age group j, this expression also resolves the index number problem. By substituting equation (3) into equation (4), we get:

$$\begin{aligned}\bar{Y}^{ND}-\bar{Y}^{D}= \; & \sum_{j=1}^{K}\bar{p}_j[\overline{F(X_{NDj}\beta_j)}-\overline{F(X_{Dj}\beta_j)}]+\sum_{j=1}^{K}\bar{p}_j[\overline{F(X_{NDj}\beta_{NDj})}-\overline{F(X_{NDj}\beta_j)}] \\ & +\sum_{j=1}^{K}\bar{p}_j[\overline{F(X_{Dj}\beta_j)}-\overline{F(X_{Dj}\beta_{Dj})}]+\sum_{j=1}^{K}\bar{Y}_j^{ND}(\bar{p}_{NDj}-\bar{p}_j) \\ & +\sum_{j=1}^{K}\bar{Y}_j^{D}(\bar{p}_j-\bar{p}_{Dj}) \end{aligned} \quad (5)$$

The first three terms are the decompositions of the within age group gaps. The first term is the proportion of the within age group employment or school attendance gaps that is due to differences in observed characteristics, whereas the unexplained part of this gap is taken into account by the second and third terms. The last two terms are differences in the employment gap or the school enrollment gap due to different age structures of disabled and non-disabled persons. This decomposition is very useful when focusing on particular age groups. For instance, as the employment gap between the disabled and non-disabled may evolve across age groups, so might discrimination. Hence, policy response to discrimination should focus on those particular age groups in which discrimination is the highest. On the other hand, decomposing the employment gap without taking into account age group differences would confound discrimination with differences in employment determination across age groups and differences in age structures of disabled and non-disabled persons.

A limitation of this decomposition method is that there are several competing reasons why the employment rate or school attendance rate should be lower among the disabled. First, disability may lower productivity so that disabled persons may be less successful in finding a job or pursuing studies. Second, the disabled may face discrimination so that they are less able to be employed or attend school. The unexplained part of the employment or school enrollment gaps may thus be due to both disability and discrimination.

Some authors have proposed to separate the effects of disability and the effects of discrimination by using proper control and treatment groups. On the one hand, Johnson and Lambrinos (1985) and Baldwin and Johnson (1994) have tried to identify people with disabilities who likely face no discrimination, so that they can be compared to other disabled persons. The pure discrimination effect could thus be measured by the difference between both groups. On the other hand, DeLeire (2001) and Jones (2006) propose to measure the discrimination effect by comparing disabled persons who are not affected in terms of productivity to non-disabled persons. However, these methods require specific questions unavailable in census data. Hence, knowing how much of the unexplained gaps in employment or school enrollment are due to the disability effect and discrimination effect is out of the scope of this paper. For policy purposes, however, decomposing the employment and school enrollment gaps into their explained and residual components is of particular interest if the focus is on compensating handicaps. Indeed, in presence of large unexplained differences between disabled and non-disabled persons in terms of access to school or to the labor market, policies aiming to alleviate vulnerability and poverty with conventional targeting instruments such as a proxy means testing–which is based on observed characteristics–may indeed be unsuccessful in compensating the disabled unless the disabled are specifically targeted.

3 The Disability Profile from the Cape Verdean Census

The Cape Verdean census is used to implement the previous methodology. In order to describe this data, this section first presents the disability variable that is available in the census and, second, provides a disability profile in which disability incidence is measured for different population categories.

3.1 The disability variable in census data

Most developing countries conduct a census at regular intervals of around ten years. Questions on disability have been introduced in these censuses, although only a minor part of the population seems to be concerned by disability: around 1% in West African countries, while disability incidence is estimated at around 10% of the world's population. These variations can be due to several factors in connection with data collection and definition of the disability variable (Mont, 2007). For these reasons, harmonization is required in order to analyze the data, and some important issues have to be tackled, such as non responses and/or difficulties in coding answers on handicap (e.g. multi-handicap) or measurement error due for instance to the fact that one single person is responding for the rest of the family.

Despite their apparent limitation in describing disability, census data allow for a systematic description of this phenomenon in West Africa. Comparisons between countries are possible because of the great similarity of questionnaires. Table 1 presents disability incidences for six West African countries including Cape Verde. Types of handicaps have been grouped into four principal categories: 'blind', including people with vision problems, 'deaf/mute', including people with speaking or hearing problems, 'disabled', including people with physical infirmities, and 'mental deficiency'. Compared to other countries' questionnaires, the Cape Verdean census questionnaire addresses all types of handicaps. Furthermore, several handicaps can be declared for one person. However, this does not clearly explain why the disability incidence of 3.24% in Cape Verde is higher than in the five other countries, since the definition of handicap is very similar in several other countries such as Niger and the Ivory Coast, which are poorer, yet declare a lower rate of disability (respectively 0.72% and 0.55%).

It is important to enumerate disabled persons, but it is even more crucial to know the extent to which observed disability leads to discrimination related to the social insertion of individuals. Indeed, more than a monetary poverty status, what most characterizes disabled persons as a group is their vulnerability and risk of low insertion in the society, notably because of difficulties in accessing the labor market or attending school.

3.2 The disability profile

The proportion of disabled persons is first explained by differences in age: in Cape Verde, 0.78% of 0-5 year old children are disabled, while 8.11% are among the 65 years old or above category (Table 2). Furthermore, as is mostly the case in African countries, disabled persons are proportionately more numerous in rural areas (3.81% versus 2.71% in urban areas). As a consequence, disability may discriminate more against people in rural areas than against those in urban areas (Table 3). We also observe that the share of individuals with a handicap is more pronounced among men (3.35%) than among women (3.11%). And finally, using household income estimates[2], we find that the share of disabled persons is higher among the poorest (4.16%) rather than among the richest (2.44%).

When considering employment rates in Table 4, we find that the difference between disabled persons and non-disabled persons averages 22.0 percentage points. In rural areas, this difference is 22.5, while in urban areas it is 22.9 percentage points. It is thus unclear whether disability discriminates more against people living in urban areas than against those living in rural areas when looking at employment rates. When considering the employment gap between disabled and non-disabled persons according to quintile of income, it appears that this gap amounts to respectively 22.6 percentage points for the poorest quintile and 24.1 percentage points for the richest quintile.

We also look at the difference between the school enrollment rate of disabled persons and that of non-disabled persons. Table 5 shows that this gap averages 16.0 percentage points at a national level. The school enrollment gap is 15.3 percentage points in rural areas and 16.5 percentage points in urban areas. It is 14.7 percentage points among the poorest households and 15.4 percentage points among the richest.

Another important feature of these gaps is their age profile. Indeed, while disability rates are explained by differences in age, disability has not the same

[2]These estimates have been obtained from a standard method of imputation. Starting with a log linear model of income determination: $lny_{i(s)} = x^{'}_{i(s)}\beta + e_{i(s)}$, where $y_{i(s)}$ is the income of household $i(s)$ from survey s, $x_{i(s)}$ is a vector of explanatory variables and $e_{i(s)}$ is an error term that is supposed to be i.i.d., this model is estimated on the 2001-02 Cape Verdean LSMS. Then, using poverty mapping methodology proposed by Elbers et al. (2003), the combination of $\hat{e}_{i(c)}$ and $\hat{\beta}$, along with the available variables $x_{i(c)}$ for individual $i(c)$ in census c, yields: $ln\hat{y}_{i(c)} = x^{'}_{i(c)}\hat{\beta} + \hat{e}_{i(c)}$, an income estimate for each individual $i(c)$ in the 2000 Cape Verdean census.

consequences at a young age (education barrier), an intermediary age (employment barrier) or a more advanced age, since for this last category disability rates are higher but the consequences on the standard of living could be mitigated by family solidarity.

It is thus important to know in what circumstances disability makes it more difficult to get a job or to go to school. Whereas it is not possible to be informed directly on the degree of inaptitude (to work or to go to school) due to disability, we choose to assess the impact of disability on both employment and school enrollment using regression analysis.

3.3 Regressions

We estimate simple probit models in order to conduct multivariate analysis of the determinants of both employment and school attendance. We consider two equations, one for urban areas and the other for rural areas, allowing for interaction effects:

$$y_U^* = \gamma_{1U} + \gamma_{2U}d + \gamma_{dU}xd + \gamma_U Z + \varepsilon_U \quad \text{(Urban)} \tag{6}$$

$$y_R^* = \gamma_{1R} + \gamma_{2R}d + \gamma_{dR}xd + \gamma_R Z + \varepsilon_R \quad \text{(Rural)} \tag{7}$$

The latent variable y_J^*, with $J = U, R$, is impacted by two independent variables x and d, where d is a dichotomous variable whose value is 1 if the person is disabled and 0 otherwise, an interaction term xd, a vector of additional independent variables Z, and an error term ε_J. As we want to know the extent to which disability interacts with other variables, we are interested in estimating an interaction effect that corresponds to the cross derivative of the expected value of the binary dependent variable y_J:

$$\frac{\partial^2 \Phi(\cdot)}{\partial x \partial d} = \gamma_{dJ}\Phi^{'}(\cdot) + (\gamma_{1J} + \gamma_{dJ}d) + (\gamma_{2J} + \gamma_{dJ}x)\Phi^{''}(\cdot), \tag{8}$$

where Φ is the standard normal cumulative distribution function, with the conditional mean of the dependent variable being:

$$E[y_j|x, d, Z] = \Phi(\gamma_{1J} + \gamma_{2J}d + \gamma_{dJ}xd + \gamma_J Z) = \Phi(\cdot). \tag{9}$$

As pointed out by Ai and Norton (2003), in nonlinear models the interaction effect should not be confused with the marginal effect of the interaction term noted $\frac{\partial\Phi(\cdot)}{\partial(xd)} = \gamma_{dJ}\Phi'(\cdot)$.[3]

When estimating equations (6) and (7) we find that, on average, disability does not significantly modify the effect of other covariates on either employment or school enrollment.[4] However, although seldom significant in average, interaction effects can be estimated for different values of the covariates. For instance, in order to visualize the effect of age and its interaction with disability, we draw several profiles of employment rate and school enrollment rate over age for both disabled and non-disabled persons, located in urban areas or in rural areas (Figs 1 and 2). All variables except age are fixed to their average value. Confidence intervals at the 5% level are reported in these graphs. The Figures show significant gaps between disabled and non-disabled persons. In urban areas, the employment gap is not significant at younger ages; it first increases and then decreases across age groups. In rural areas, a significant employment gap between the disabled and non-disabled is noticeable at younger ages on the labor market, after which we also observe an inverted U curve over the life cycle. The school enrollment gap, for its part, seems to be rather stable across age groups in both rural and urban areas.

4 Empirical Results

In this section, the previous methodology of decomposition of the employment and school enrollment differentials is applied to the Cape Verdean census data. First, we run regressions on employment and school enrollment with different samples: disabled persons, non-disabled persons and a pooled sample. Second, the coefficient estimates are used to perform the decompositions across age

[3] Standard errors and z-statistics for interaction effects can be computed using traditional software (cf. Norton et al., 2004).

[4] Equations of employment and school enrollment, not reported here but available upon request, use different independent variables: number of infant, (number of infant)^2, number of children, (number of children)^2, number of adults, (number of adults)^2, age, age squared, being single and the level of education (for the employment equation only), and characteristics of household heads (education, age, age squared and professional activity); the school enrollment equation also uses the quintile of predicted income as a covariate. Furthermore, all these variables have been crossed with the disability variable.

groups. Last, to check for robustness, we rerun the decompositions by taking into account misclassification errors of the disability variable.

4.1 Decomposition of the school enrollment differential

The choice of whether to go to school is modeled using maximum likelihood estimates of school attendance. Results from logit regressions are presented in Tables 6 and 7. There appear clear differences between coefficient estimates from disabled regression, non-disabled regression and pooled regression. Hence, decomposition of the school enrollment gap should differ according to which coefficient estimates (or weights) are used for the decomposition. Tables 8 and 9 present the decomposition results for different age groups. There are only slight differences between the three methods of weighting the decomposition (disabled, non-disabled or pooled regressions coefficients). Overall, most of the gap is not explained by the difference in observed characteristics. The school attendance differential between disabled and non-disabled persons is mostly due to the differences between returns to observed characteristics, that is, discrimination and unobserved differences in productivity. Tables 8 and 9 show that this finding is true for each age group, while Table 11 shows that differences in age structures between the disabled and the non-disabled–as shown in Table 10–have no impact on the school enrollment gap.

4.2 Decomposition of the employment differential

Another exercise is to decompose the employment gap. Logit regression coefficients are presented in Tables 12 and 13. The estimated coefficients from the disabled and non-disabled regressions still appear very different. So, when decomposing the employment gap in Tables 14 and 15 we find that the part explained by differences in observed characteristics is small compared to the residual part. What is more, differences in age structure have a small impact on the employment gap (Table 16). Hence, again the employment gap should be explained by discrimination and unobserved differences in productivity.

4.3 Sensitivity analyses of the misclassified disability variable

In order to check the sensitivity of the previous decomposition to misclassification error of the disability variable, we use the modified maximum likelihood approach proposed by Hausman et al. (1998).[5] Let d^* be an unobserved latent variable for the disability status, given by:

$$d^* = \beta X + \delta W + u, \tag{10}$$

where X is a vector of covariates that may affect both the response and the probability that the response is observed correctly, W is a vector of covariates that are assumed to affect the true response but do not affect the probability of misclassification, and u is an i.i.d. error term.

As in Caudill and Mixon (2005), we only consider the possibility that some people report themselves to be non-disabled when they are actually disabled. The misclassification probability of the binary disability variable is:

$$\alpha(X) = Pr(d = 0|\tilde{d} = 1, X), \tag{11}$$

where $\tilde{d}$ is the true (but unobserved) disability variable. We assume that $\alpha(X) = \Phi(\gamma X)$ where Φ is the standard normal cumulative distribution function. Noting P the probability of being non-disabled, and $P^* = \alpha(X) + (1 - \alpha(X))P$ the probability that someone is reported as non-disabled, the likelihood function for the model with misclassification error is given by:

$$lnL = \sum_{i=1}^{n} d_i ln(P_i^*) + (1 - d_i) ln(1 - P_i^*). \tag{12}$$

Table 17 presents both the estimates of the basic logit model and the estimates of the logit model with misclassification error for people between 15 and 64 years of age. The Lagrange multiplier statistic indicates that the misclassification is significantly different from zero at the 1 percent level. Furthermore, the misclassification probability is significant, but it does not seem to vary across gender and residence areas. Function $\alpha(Intercept)$ is estimated to be 0.174 that is the probability of not declaring disability when actually disabled. Hence, according to these results, many persons should be considered as disabled in Cape Verde although they are not declared as such. It is thus possible to predict the percentage of disabled persons corrected for misclassification error. According to the model, we consider someone as disabled when he/she is reported as disabled or his/her estimated probability of being disabled is higher than the observed frequency of the disabled in the country, restricting the misclassification probability to being

[5] See also Lewbel (2000).

null. As a result, Table 18 shows that the percentage of estimated disabled persons is almost twice as large as the actual percentage of disabled persons. This difference between estimated and actual percentages is greater among older persons and among men. So, using this estimated disability status, we perform a new decomposition of the employment gap in Table 19. This gap appears to be larger than the previous estimated one, especially among men and among older persons. Furthermore, when decomposing this gap into an explained component and a residual component, we find that the explained part of the employment gap is more pronounced than it was previously: it accounts for a major part of the gap among older men, and thus differences in age structure have a more significant impact on this gap.

5 Conclusion

In this paper, we provide estimates of the employment and school enrollment gaps between disabled and non-disabled persons using the last Cape Verdean census. Using decomposition techniques, we find that the unexplained component accounts for most of these gaps, whatever the age group considered. Differences in age structure between the disabled and non-disabled are not going to explain these gaps, either. Going one step further, to check for the robustness of these findings, we estimate a model with misclassification error in order to predict the disability status of 15-64 year old people. We consider the possibility that disability is under-reported. Using a modified estimated disability variable, we find that the explained part of the employment gap is larger than previously estimated, especially among older men. However, the residual part of the gap is still prominent when considering the whole population. A consequence of these findings is that policies that would target the poor or the vulnerable based on observable characteristics would not succeed in compensating handicaps, unless they specifically target the disabled. What is more, disability may have an impact on social integration: from education to employment, this effect appears to be cumulative over the life cycle, with lower access to the labor market for disabled persons even at the earliest stages of employability. Policies aiming to compensate these handicaps should thus focus on young children and young adults to overcome persistent inequality. These findings should however be further assessed using other data in order to isolate the effect of disability on productivity and thus on employment and education differentials.

6 References

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Table 1: Disability incidence in six West African countries

In %	Without handicap	With handicap	Blind	Deaf/mute	Disabled	Mental deficiency	Others
Cape Verde**	96.76	3.24	0.66	0.55	1.90	0.36	-
Guinea*	98.06	1.94	-	-	-	-	-
Mauritania*	98.23	1.77	0.39	0.29	0.82	0.20	0.06
Mali*	99.14	0.86	0.36	0.15	0.17	0.05	0.13
Niger**	99.28	0.72	0.10	0.29	0.25	0.21	0.24
Ivory Coast **	99.45	0.55	0.20	0.21	0.29	-	0.16

Source: Own computations using population censuses (Cape Verde 2000, Ivory Coast 1998, Guinea 1996, Mali 1998, Mauritania 2001 and Niger 2001). *Notes:* *Main handicap is declared; **Several handicaps can be declared for one person.

Table 2: Share of individuals with various handicaps by age and gender

In %	Age						Gender		
Type of handicap	0-5	6-14	15-25	26-45	46-64	>65	Men	Women	Total
Blind	0.12	0.35	0.33	0.35	0.80	1.76	0.64	0.67	0.65
Deaf/mute	0.17	0.41	0.30	0.41	0.50	1.00	0.57	0.53	0.55
Disabled	0.52	0.92	1.23	1.67	2.64	5.08	2.00	1.80	1.90
Mental deficiency	0.04	0.20	0.31	0.55	0.61	0.74	0.38	0.33	0.35
Any handicap	0.78	1.77	2.04	2.84	4.31	8.11	3.35	3.11	3.22

Source: Own computations using 2000 Cape Verdean population census.

Table 3: Share of individuals with various handicaps by quintile and location

In %	Quintile					Location		
Type of handicap	Poorest	2nd	3rd	4th	Richest	Urban	Rural	National
Blind	0.85	0.65	0.68	0.61	0.48	0.54	0.78	0.65
Deaf/mute	0.78	0.61	0.51	0.43	0.41	0.41	0.71	0.55
Disabled	2.45	1.99	1.79	1.81	1.41	1.63	2.20	1.90
Mental deficiency	0.43	0.37	0.32	0.33	0.31	0.30	0.41	0.35
Any handicap	4.16	3.37	3.10	3.00	2.44	2.71	3.81	3.22

Source: Own computations using 2000 Cape Verdean population census.

Table 4: Employment rates by quintile and location

In %	Quintile					Location		
Type of handicap	Poorest	2nd	3rd	4th	Richest	Urban	Rural	National
Individuals aged 15 and above								
Blind	36.23	31.92	31.74	31.51	28.91	29.51	34.74	32.41
Deaf/mute	39.25	36.48	35.50	26.50	27.59	26.05	39.28	34.01
Disabled	29.37	29.85	27.28	24.74	21.84	24.45	29.25	27.06
Mental deficiency	18.24	15.47	13.08	16.46	12.32	14.41	16.22	15.40
Any handicap	30.72	29.44	27.71	25.24	22.67	24.39	30.21	27.61
No handicap	53.33	52.44	50.50	46.14	46.74	47.28	52.66	49.61

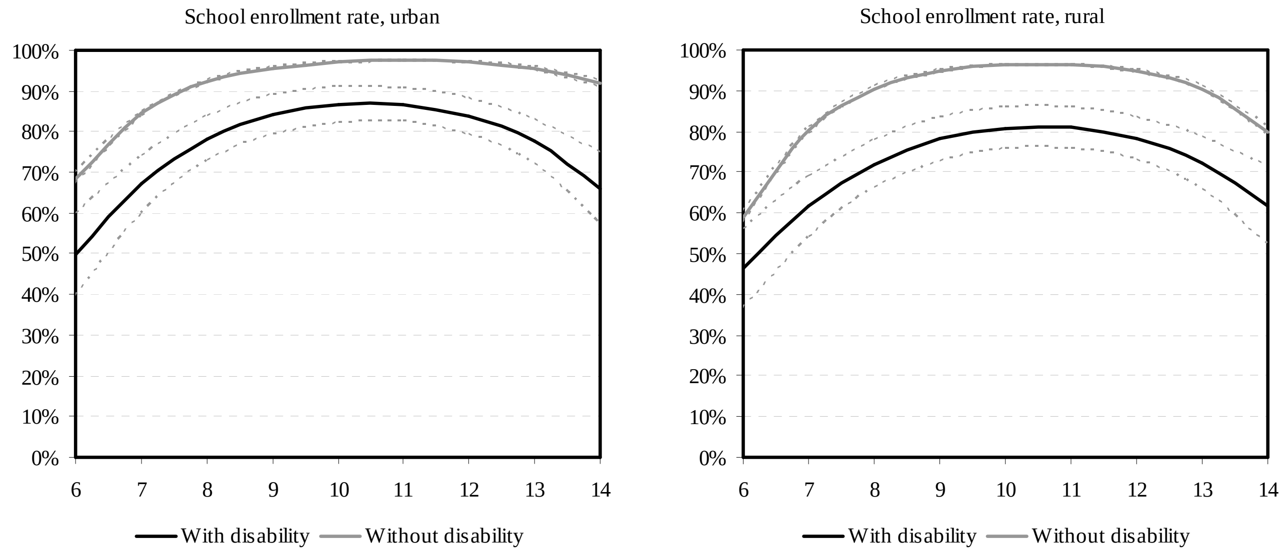
Source: Own computations using 2000 Cape Verdean population census. Note: Individuals are 15 to 64 years old.

Table 5: School enrollment rates by quintile and location

In %	Quintile					Location		
Type of handicap	Poorest	2nd	3rd	4th	Richest	Urban	Rural	National
Children aged between 6 and 14								
Blind	83.00	86.84	85.19	91.89	92.31	87.72	86.43	87.03
Deaf/mute	68.64	70.71	71.83	80.70	79.31	71.94	72.77	72.46
Disabled	65.64	64.22	68.42	82.05	73.33	71.22	68.67	69.93
Mental deficiency	51.92	59.26	46.67	68.29	78.13	65.69	54.10	59.38
Any handicap	68.24	68.76	70.03	82.29	78.54	73.85	71.25	72.45
No handicap	82.93	85.90	88.87	92.46	93.95	90.36	86.55	88.44

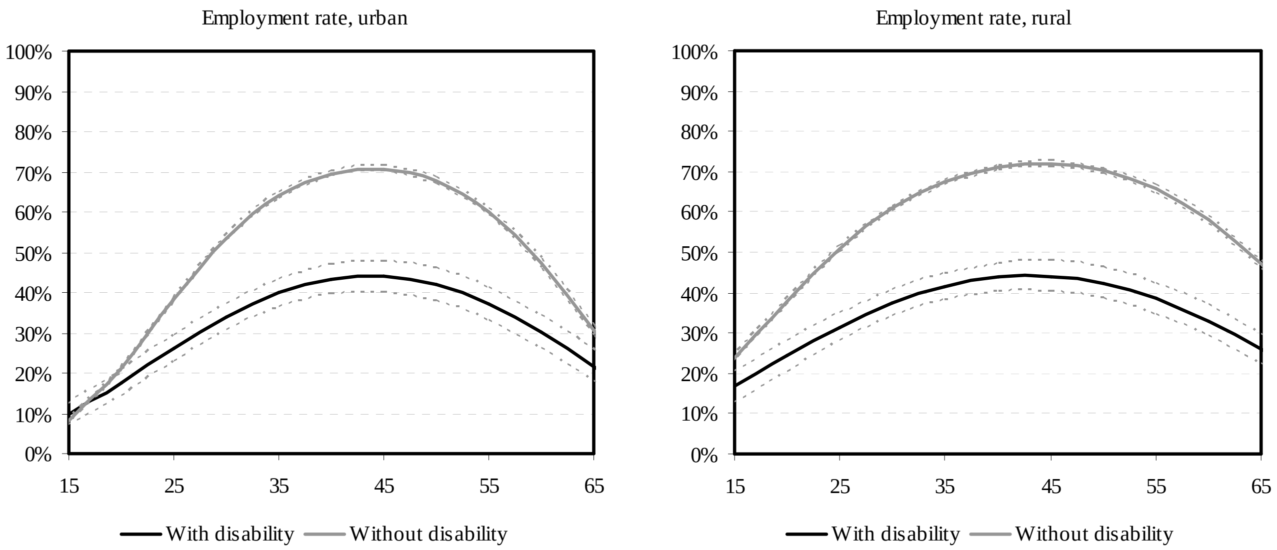
Source: Own computations using 2000 Cape Verdean population census. Note: Children are 6 to 14 years old.

Fig. 1: Age profile of school enrollment rate



Source: Own computations using 2000 Cape Verdean population census.

Fig. 2: Age profile of employment rate



Source: Own computations using 2000 Cape Verdean population census.

Table 6: School attendance logit regressions (urban)

	All			Among disabled			Among non-disabled		
	Coeff. Estimate	Marginal Effect	P-value	Coeff. Estimate	Marginal Effect	P-value	Coeff. Estimate	Marginal Effect	P-value
Constant	-12.001	0.000	<0.001	-10.554	0.000	<0.001	-12.050	0.000	<0.001
Disabled	-1.364	-0.107	<0.001	-	-	-	-	-	-
Number of children 0-6 years	-0.024	-0.002	0.427	-0.132	-0.023	0.560	-0.022	-0.002	0.418
(Number of children 0-6 years)^2	-0.006	-0.001	0.456	0.037	0.006	0.055	-0.006	0.000	0.041
Number of children 6-14 years	0.085	0.007	0.021	0.394	0.068	0.077	0.077	0.006	0.004
(Number of children 6-14 years)^2	-0,018	0.000	0.002	-0.061	-0.011	0.581	-0.017	-0.001	0.576
Number of persons >14 years	0.020	0.002	0.489	0.095	0.016	0.597	0.017	0.001	0.381
(Number of persons >14 years)^2	0.002	0.000	0.450	-0.010	-0.002	<0.001	0.003	0.000	<0.001
Age	2.462	0.193	<0.001	2.037	0.352	<0.001	2.468	0.190	<0.001
Age^2	-0.113	-0.009	<0.001	-0.098	-0.017	0.624	-0.113	-0.009	<0.001
Male	-0.137	-0.011	<0.001	0.079	0.014	0.126	-0.146	-0.011	<0.001
2nd quintile	0.196	0.015	<0.001	0.444	0.077	0.666	0.191	0.015	<0.001
3rd quintile	0.384	0.030	<0.001	0.113	0.019	0.128	0.397	0.030	<0.001
4th quintile	0.604	0.047	<0.001	0.416	0.072	0.026	0.611	0.047	<0.001
5th quintile	0.818	0.064	<0.001	0.741	0.128	0.254	0.820	0.063	<0.001
Head with primary education	0.333	0.026	<0.001	0.238	0.041	0.365	0.338	0.026	<0.001
Head with secondary education	0.515	0.040	<0.001	0.347	0.060	0.722	0.526	0.040	<0.001
Head with tertiary education	0.410	0.032	<0.001	-0.228	-0.039	0.877	0.430	0.033	<0.001
Age of the head	0.038	0.003	<0.001	0.006	0.001	0.952	0.038	0.003	<0.001
(Age of the head)^2	0.000	0.000	<0.001	0.000	0.000	0.106	0.000	0.000	0.456
Head agro-wage earner	-0.185	-0.015	0.299	-1.957	-0.338	0.641	-0.137	-0.011	0.440
Head non agro-independent	-0.037	-0.003	0.486	0.131	0.023	0.184	-0.042	-0.003	0.001
Head non agro-wage earner	0.190	0.015	<0.001	0.395	0.068	0.657	0.181	0.014	0.488
Head unemployed	-0.063	-0.005	0.430	-0.182	-0.031	0.274	-0.057	-0.004	0.604
Head at home	0.050	0.004	0.445	0.369	0.064	0.982	0.035	0.003	0.725
Head student	-0.052	-0.004	0.867	13.211	3.150	0.063	-0.109	-0.008	0.237
Head inactive	-0.055	-0.004	0.448	0.663	0.114	<0.001	-0.088	-0.007	<0.001

Source: Own computations using 2000 Cape Verdean population census.

Table 7: School attendance logit regressions (rural)

	All			Among disabled			Among non-disabled		
	Coeff. Estimate	Marginal Effect	P-value	Coeff. Estimate	Marginal Effect	P-value	Coeff. Estimate	Marginal Effect	P-value
Constant	-13.524	0.000	<0.001	-7.592	0.000	<0.001	-13.766	0.000	<0.001
Disabled	-1.168	-0.120	<0.001	-	-	-	-	-	-
Number of children 0-6 years	-0.105	-0.011	<0.001	-0.410	-0.078	0.130	-0.095	-0.010	0.005
(Number of children 0-6 years)^2	0.028	-0.002	0.002	0.103	0.020	0.223	0.026	0.003	<0.001
Number of children 6-14 years	0.114	0.012	0.002	-0.261	-0.049	0.318	0.125	0.013	0.001
(Number of children 6-14 years)^2	-0,02	-0.018	0.003	0.04	0.036	0.032	-0.02	-0.020	0.079
Number of persons >14 years	0.060	0.006	0.037	0.375	0.071	0.020	0.052	0.005	0.935
(Number of persons >14 years)^2	-0.002	0.000	0.629	-0.047	-0.009	<0.001	0.000	0.000	<0.001
Age	2.916	0.300	<0.001	1.682	0.318	<0.001	2.958	0.299	<0.001
Age^2	-0.139	-0.014	<0.001	-0.080	-0.015	0.312	-0.141	-0.014	0.202
Male	-0.028	-0.003	0.284	0.143	0.027	0.664	-0.034	-0.003	<0.001
2nd quintile	0.181	0.019	<0.001	-0.079	-0.015	0.424	0.190	0.019	<0.001
3rd quintile	0.284	0.029	<0.001	-0.180	-0.034	0.995	0.300	0.030	<0.001
4th quintile	0.451	0.046	<0.001	-0.002	0.000	0.346	0.468	0.047	<0.001
5th quintile	0.770	0.079	<0.001	-0.539	-0.102	0.060	0.837	0.085	<0.001
Head with primary education	0.320	0.033	<0.001	0.309	0.059	0.106	0.321	0.033	<0.001
Head with secondary education	0.907	0.093	<0.001	1.032	0.195	0.982	0.901	0.091	0.013
Head with tertiary education	1.512	0.156	0.004	14.093	3.941	0.896	1.308	0.132	0.006
Age of the head	0.018	0.002	0.007	-0.005	-0.001	0.897	0.019	0.002	0.084
(Age of the head)^2	0.000	0.000	0.099	0.000	0.000	0.267	0.000	0.000	0.120
Head agro-wage earner	0.171	0.018	0.094	0.726	0.138	0.068	0.161	0.016	<0.001
Head non agro-independent	0.182	0.019	<0.001	0.395	0.075	0.432	0.175	0.018	<0.001
Head non agro-wage earner	0.169	0.017	<0.001	0.165	0.031	0.933	0.172	0.017	0.653
Head unemployed	0.027	0.003	0.660	0.023	0.004	0.952	0.028	0.003	<0.001
Head at home	0.267	0.027	<0.001	-0.015	-0.003	<0.001	0.281	0.028	0.038
Head student	2.099	0.216	0.042	0.000	0.000	0.584	2.132	0.216	0.160
Head inactive	0.071	0.007	0.143	0.141	0.027	<0.001	0.069	0.007	<0.001

Source: Own computations using 2000 Cape Verdean population census.

Table 8: Decomposition of school enrollment gap (urban)

	All			Male			Female		
	Gap	Explained	Residuals	Gap	Explained	Residuals	Gap	Explained	Residuals
All Ages									
Pooled regression	0.16	0.00	0.16	0.16	0.01	0.15	0.17	0.00	0.17
Disabled only		0.00	0.16		0.01	0.15		0.00	0.18
Non-disabled only		0.00	0.16		0.01	0.15		0.00	0.17
6-8 years									
Pooled regression	0.16	0.00	0.16	0.16	0.01	0.15	0.16	-0.01	0.17
Disabled only		-0.01	0.17		0.00	0.16		0.00	0.16
Non-disabled only		0.00	0.16		0.01	0.15		-0.01	0.17
9-11 years									
Pooled regression	0.13	0.00	0.13	0.11	0.00	0.11	0.14	0.00	0.14
Disabled only		0.00	0.13		-0.03	0.14		0.00	0.15
Non-disabled only		0.00	0.13		0.00	0.11		0.00	0.14
12-14 years									
Pooled regression	0.21	0.01	0.19	0.19	0.01	0.18	0.23	0.01	0.21
Disabled only		0.00	0.20		0.02	0.17		0.01	0.22
Non-disabled only		0.01	0.20		0.01	0.18		0.01	0.22

Source: Own computations using 2000 Cape Verdean population census.

Table 9: Decomposition of school enrollment gap (rural)

	All			Male			Female		
	Gap	Explained	Residuals	Gap	Explained	Residuals	Gap	Explained	Residuals
All Ages									
Pooled regression	0.15	0.00	0.16	0.14	-0.005	0.15	0.17	0.00	0.17
Disabled only		-0.01	0.16		-0.01	0.15		-0.01	0.18
Non-disabled only		0.00	0.16		0.00	0.15		0.00	0.17
6-8 years									
Pooled regression	0.16	0.00	0.16	0.13	0.00	0.14	0.19	0.01	0.19
Disabled only		0.00	0.16		0.01	0.13		-0.01	0.20
Non-disabled only		0.00	0.16		0.00	0.14		0.01	0.19
9-11 years									
Pooled regression	0.17	0.00	0.17	0.17	0.00	0.17	0.17	0.00	0.17
Disabled only		0.01	0.16		-0.01	0.17		-0.01	0.18
Non-disabled only		0.00	0.17		0.00	0.17		0.00	0.17
12-14 years									
Pooled regression	0.14	0.00	0.15	0.13	0.00	0.13	0.16	0.00	0.16
Disabled only		-0.01	0.15		-0.01	0.14		-0.02	0.18
Non-disabled only		0.00	0.15		0.00	0.13		0.00	0.16

Source: Own computations using 2000 Cape Verdean population census.

Table 10: Percentages of disabled persons, by age group

In %	Urban			Rural		
	All	Male	Female	All	Male	Female
All Ages	2.38	2.58	2.20	3.35	3.65	3.09
6-8 years	1.58	1.68	1.48	1.72	1.89	1.55
9-11 years	1.68	1.67	1.68	1.84	1.98	1.70
12-14 years	1.70	1.93	1.47	2.17	2.40	1.94
15-24 years	1.75	2.06	1.46	2.45	2.84	2.04
25-34 years	2.28	2.53	2.03	3.66	4.19	3.16
35-44 years	2.97	3.26	2.70	4.72	5.68	4.03
45-54 years	4.74	4.98	4.54	7.29	9.52	6.18
55-64 years	6.89	7.65	6.38	9.31	10.71	8.49

Source: Own computations using 2000 Cape Verdean population census.

Table 11: Decomposition of school enrollment gap according to differences in age structures

	Urban			Rural		
	All	Male	Female	All	Male	Female
Gap	0.16	0.16	0.17	0.15	0.14	0.17
Pooled regression coefficient						
Within age group explained	0.00	0.01	0.00	0.00	0.00	0.00
Within age group unexplained	0.16	0.15	0.18	0.16	0.15	0.17
Age structure difference	0.00	0.01	0.00	0.00	0.00	0.00
Disabled regression coefficient						
Within age group explained	0.00	0.00	0.00	0.00	0.00	-0.01
Within age group unexplained	0.17	0.16	0.18	0.16	0.15	0.19
Age structure difference	0.00	0.01	0.00	0.00	0.00	0.00
Non-disabled regression coefficient						
Within age group explained	0.00	0.01	0.00	0.00	0.00	0.00
Within age group unexplained	0.16	0.15	0.18	0.16	0.15	0.17
Age structure difference	0.00	0.01	0.00	0.00	0.00	0.00

Source: Own computations using 2000 Cape Verdean population census.

Table 12: Employment logit regressions (urban)

	All			Among disabled			Among non-disabled		
	Coeff. Estimate	Marginal Effect	P-value	Coeff. Estimate	Marginal Effect	P-value	Coeff. Estimate	Marginal Effect	P-value
Constant	-5.503	0.000	<0.001	-3.635	0.000	<0.001	-5.569	0.000	<0.001
Disabled	-1.056	-0.196	<0.001	-	-	-	-	-	-
Number of children 0-6 years	0.028	0.005	0.051	0.175	0.031	0.711	0.024	0.004	0.101
(Number of children 0-6 years)^2	-0.007	-0.001	0.103	-0.012	-0.002	0.884	-0.007	-0.001	0.116
Number of children 6-14 years	-0.092	-0.017	<0.001	-0.011	-0.002	0.714	-0.096	-0.018	<0.001
(Number of children 6-14 years)^2	0,012	0.002	<0.001	0.006	0.001	0.423	0.012	0.002	<0.001
Number of persons >14 years	-0.027	-0.005	0.025	-0.057	-0.010	0.660	-0.028	-0.005	0.023
(Number of persons >14 years)^2	0.003	0.001	0.003	0.003	0.001	<0.001	0.003	0.001	0.003
Age	0.342	0.063	<0.001	0.182	0.032	<0.001	0.348	0.064	<0.001
Age^2	-0.004	-0.001	<0.001	-0.002	0.000	0.001	-0.004	-0.001	<0.001
Male	0.711	0.132	<0.001	0.277	0.050	<0.001	0.726	0.134	<0.001
Single	0.012	0.002	0.460	-0.341	-0.061	0.380	0.029	0.005	0.086
Primary education	0.285	0.053	0.148	0.960	0.172	0.505	0.255	0.047	0.208
Secondary education	-0.244	-0.045	0.225	0.753	0.135	0.291	-0.278	-0.051	0.178
Tertiary education	0.024	0.004	0.911	1.288	0.231	0.880	-0.019	-0.004	0.931
Head of household	-0.314	-0.058	<0.001	0.096	0.017	0.700	-0.348	-0.064	<0.001
Head with primary education	-0.175	-0.032	<0.001	-0.050	-0.009	0.161	-0.179	-0.033	<0.001
Head with secondary education	-0.121	-0.022	<0.001	-0.338	-0.061	0.759	-0.117	-0.022	<0.001
Head with tertiary education	0.107	0.020	0.015	0.119	0.021	0.244	0.115	0.021	0.010
Age of the head	-0.049	-0.009	<0.001	-0.027	-0.005	0.268	-0.050	-0.009	<0.001
(Age of the head)^2	0.000	0.000	<0.001	0.000	0.000	0.640	0.000	0.000	<0.001
Head agro-wage earner	0.364	0.067	<0.001	0.273	0.049	0.219	0.362	0.067	<0.001
Head non agro-independent	0.260	0.048	<0.001	-0.258	-0.046	0.515	0.274	0.051	<0.001
Head non agro-wage earner	0.253	0.047	<0.001	-0.138	-0.025	0.157	0.263	0.049	<0.001
Head unemployed	0.086	0.016	0.059	-0.428	-0.077	0.028	0.096	0.018	0.038
Head at home	0.165	0.030	<0.001	-0.543	-0.097	0.501	0.182	0.034	<0.001
Head student	-0.721	-0.133	<0.001	0.713	0.128	0.054	-0.742	-0.137	<0.001
Head inactive	0.034	0.006	0.344	-0.432	-0.077	0.345	0.043	0.008	0.241

Source: Own computations using 2000 Cape Verdean population census.

Table 13: Employment logit regressions (rural)

	Pooled Regression			Handicapped Regression			Non-Handicapped Regression		
	Coeff. Estimate	Marginal Effect	P-value	Coeff. Estimate	Marginal Effect	P-value	Coeff. Estimate	Marginal Effect	P-value
Constant	-3.443	0.000	<0.001	-1.655	0.000	0.012	-3.538	0.000	<0.001
Disabled	-1.115	-0.221	<0.001	-	-	-	-	-	-
Number of children 0-6 years	0.080	0.016	<0.001	0.196	0.040	0.048	0.077	0.015	<0.001
(Number of children 0-6 years)^2	-0.015	-0.003	<0.001	-0.055	-0.011	0.484	-0.014	-0.003	0.002
Number of children 6-14 years	-0.059	-0.012	<0.001	-0.052	-0.011	0.124	-0.065	-0.013	<0.001
(Number of children 6-14 years)^2	0,008	0.002	0.015	0.028	0.006	0.903	0.008	0.002	0.016
Number of persons >14 years	-0.006	-0.001	0.694	-0.009	-0.002	0.947	-0.011	-0.002	0.474
(Number of persons >14 years)^2	0.001	0.000	0.701	0.000	0.000	<0.001	0.001	0.000	0.526
Age	0.211	0.042	<0.001	0.105	0.022	<0.001	0.218	0.043	<0.001
Age^2	-0.003	-0.001	<0.001	-0.001	0.000	<0.001	-0.003	-0.001	<0.001
Male	0.917	0.182	<0.001	0.429	0.088	<0.001	0.945	0.187	<0.001
Single	0.003	0.001	0.864	-0.388	-0.080	0.692	0.031	0.006	0.099
Primary education	0.369	0.073	0.014	0.216	0.044	0.870	0.389	0.077	0.012
Secondary education	-0.608	-0.120	<0.001	-0.099	-0.020	0.075	-0.603	-0.119	<0.001
Tertiary education	0.697	0.138	0.002	1.509	0.310	0.659	0.582	0.115	0.014
Head of household	0.128	0.025	0.242	-0.244	-0.050	0.840	0.090	0.018	0.425
Head with primary education	-0.184	-0.036	<0.001	0.021	0.004	0.447	-0.192	-0.038	<0.001
Head with secondary education	-0.065	-0.013	0.281	-0.341	-0.070	0.968	-0.058	-0.011	0.340
Head with tertiary education	-0.030	-0.006	0.863	-11.214	-3.546	0.043	0.002	0.000	0.991
Age of the head	-0.008	-0.002	0.058	-0.040	-0.008	0.025	-0.008	-0.001	0.066
(Age of the head)^2	0.000	0.000	0.001	0.000	0.000	0.379	0.000	0.000	0.001
Head agro-wage earner	-0.416	-0.083	<0.001	-0.302	-0.062	0.163	-0.422	-0.083	<0.001
Head non agro-independent	-0.204	-0.040	<0.001	-0.206	-0.042	0.481	-0.205	-0.040	<0.001
Head non agro-wage earner	-0.275	-0.055	<0.001	-0.102	-0.021	<0.001	-0.285	-0.056	<0.001
Head unemployed	-0.957	-0.190	<0.001	-1.144	-0.235	0.002	-0.961	-0.190	<0.001
Head at home	-0.645	-0.128	<0.001	-0.503	-0.103	0.302	-0.654	-0.129	<0.001
Head student	-0.702	-0.139	0.063	1.548	0.318	<0.001	-0.835	-0.165	0.032
Head inactive	-0.597	-0.118	<0.001	-0.543	-0.111	0.450	-0.602	-0.119	<0.001

Source: Own computations using 2000 Cape Verdean population census.

Table 14: Decomposition of employment gap (urban)

	All			Male			Female		
	Gap	Explained	Residuals	Gap	Explained	Residuals	Gap	Explained	Residuals
All Ages									
Pooled regression	0.19	0.00	0.19	0.24	0.01	0.23	0.16	0.00	0.15
Disabled only		0.05	0.14		0.07	0.17		0.05	0.11
Non-disabled only		-0.01	0.20		0.00	0.24		0.00	0.16
15-24 years									
Pooled regression	0.12	-0.02	0.14	0.16	-0.02	0.17	0.08	0.00	0.08
Disabled only		0.04	0.08		0.04	0.11		0.05	0.04
Non-disabled only		-0.02	0.14		-0.02	0.18		0.00	0.08
25-34 years									
Pooled regression	0.25	0.05	0.21	0.31	0.08	0.23	0.21	0.03	0.18
Disabled only		0.12	0.14		0.16	0.16		0.10	0.11
Non-disabled only		0.04	0.22		0.07	0.25		0.03	0.18
35-44 years									
Pooled regression	0.29	0.04	0.25	0.34	0.08	0.26	0.25	0.02	0.24
Disabled only		0.09	0.20		0.13	0.21		0.07	0.18
Non-disabled only		0.03	0.26		0.07	0.27		0.01	0.24
45-54 years									
Pooled regression	0.29	0.07	0.22	0.38	0.10	0.28	0.21	0.05	0.17
Disabled only		0.08	0.21		0.13	0.25		0.06	0.16
Non-disabled only		0.06	0.23		0.08	0.30		0.04	0.18
55-64 years									
Pooled regression	0.17	0.02	0.15	0.25	0.03	0.22	0.13	0.03	0.09
Disabled only		0.02	0.15		0.03	0.21		0.03	0.09
Non-disabled only		0.02	0.15		0.02	0.22		0.03	0.10

Source: Own computations using 2000 Cape Verdean population census.

Table 15: Decomposition of employment gap (rural)

	All			Male			Female		
	Gap	Explained	Residuals	Gap	Explained	Residuals	Gap	Explained	Residuals
All Ages									
Pooled regression	0.20	-0.03	0.22	0.23	-0.03	0.26	0.18	-0.01	0.19
Disabled only		0.02	0.17		0.02	0.21		0.04	0.14
Non-disabled only		-0.04	0.23		-0.04	0.27		-0.02	0.20
15-24 years									
Pooled regression	0.13	-0.03	0.17	0.17	-0.01	0.19	0.11	-0.02	0.13
Disabled only		0.03	0.11		0.01	0.16		0.07	0.04
Non-disabled only		-0.04	0.18		-0.02	0.20		-0.04	0.15
25-34 years									
Pooled regression	0.27	0.02	0.25	0.33	0.05	0.27	0.23	0.02	0.21
Disabled only		0.09	0.17		0.12	0.21		0.10	0.13
Non-disabled only		0.00	0.26		0.03	0.29		0.01	0.22
35-44 years									
Pooled regression	0.26	0.01	0.26	0.32	0.05	0.27	0.24	0.00	0.24
Disabled only		0.05	0.21		0.10	0.22		0.03	0.21
Non-disabled only		-0.01	0.27		0.04	0.29		0.00	0.24
45-54 years									
Pooled regression	0.22	0.00	0.22	0.31	0.06	0.26	0.20	0.01	0.19
Disabled only		0.03	0.20		0.06	0.25		0.05	0.15
Non-disabled only		-0.01	0.23		0.04	0.28		0.01	0.19
55-64 years									
Pooled regression	0.22	0.00	0.22	0.28	0.03	0.25	0.20	0.02	0.19
Disabled only		0.01	0.21		0.05	0.24		0.02	0.18
Non-disabled only		0.00	0.22		0.02	0.27		0.01	0.19

Source: Own computations using 2000 Cape Verdean population census.

Table 16: Decomposition of employment gap according to differences in age structures

	Urban			Rural		
	All	Male	Female	All	Male	Female
Gap	0.19	0.24	0.16	0.20	0.23	0.18
Pooled regression coefficient						
Within age group explained	0.02	0.04	0.02	-0.01	0.02	0.00
Within age group unexplained	0.19	0.22	0.15	0.21	0.23	0.18
Age structure difference	-0.01	-0.02	-0.01	-0.01	-0.03	-0.01
Disabled regression coefficient						
Within age group explained	0.07	0.10	0.06	0.05	0.06	0.06
Within age group unexplained	0.13	0.16	0.10	0.16	0.19	0.12
Age structure difference	-0.01	-0.02	-0.01	-0.01	-0.03	-0.01
Non-disabled regression coefficient						
Within age group explained	0.01	0.03	0.01	-0.02	0.01	-0.01
Within age group unexplained	0.19	0.23	0.15	0.22	0.25	0.19
Age structure difference	-0.01	-0.02	-0.01	-0.01	-0.03	-0.01

Source: Own computations using 2000 Cape Verdean population census.

Table 17: Disability logit regression with misclassification error (among 15-64 years old)

	Basic logit		Logit with misclassification errors	
	Coeff. Estimate	P-value	Coeff. Estimate	P-value
Constant	2.3001	<0.0001	2.2163	<0.0001
Individual characteristics				
Number of children 0-6 years	0.1205	<0.0001	0.1208	<0.0001
(Number of children 0-6 years)^2	-0.0159	0.0474	-0.0160	0.0460
Number of children 6-14 years	0.0784	0.0016	0.0798	0.0014
(Number of children 6-14 years)^2	-0.0092	0.1045	-0.0095	0.0942
Number of persons >14 years	0.0343	0.1665	0.0372	0.1359
(Number of persons >14 years)^2	-0.0016	0.5099	-0.0018	0.4547
Male	-0.3732	<0.0001	-0.2571	<0.0001
Urban	0.2417	<0.0001	0.3529	<0.0001
Single	-0.3435	<0.0001	-0.3463	<0.0001
Spouse	0.2680	<0.0001	0.2684	<0.0001
Child	-0.3472	<0.0001	-0.3421	<0.0001
Parent	0.0709	0.6224	0.0516	0,7283
Sister / Brother	-0.5545	<0.0001	-0.5644	<0.0001
Grandchild	-0.1846	0.0935	-0.1700	0,1244
Son / Daughter-in-law	0.4079	0.0306	0.3476	0.0616
Niece / Nephew	-0.3706	0.0016	-0.3598	0.0023
Stepchild	-0.2968	0.0168	-0.2895	0,0208
Other	-0.3298	0.0002	-0.3363	0.0002
25-34 years old	-0.6165	<0.0001	-0.6186	<0.0001
35-44 years old	-0.8877	<0.0001	-0.8957	<0.0001
45-54 years old	-1.0350	<0.0001	-1.0514	<0.0001
55-64 years old	-0.7513	<0.0001	-0.7562	<0.0001
Primary education	2.3001	<0.0001	2.2163	<0.0001
Secondary education	1.4224	<0.0001	1.4168	<0.0001
Tertiary education	1.0714	<0.0001	1.0831	<0.0001
Agro-wage earner	0.4159	0.0219	0.4483	0.0140
Non agro-independent	0.1365	0.0239	0.1352	0.0259
Non agro-wage earner	0.0416	0.4822	0.0354	0.5515
Unemployed	-0.5804	<0.0001	-0.5726	<0.0001
At home	-0.7123	<0.0001	-0.6892	<0.0001
Student	-0.3643	0.0006	-0.3519	0,0009
Inactive	-2.5600	<0.0001	-2.5663	<0.0001
Employed	-0.2874	0.0014	-0.2694	0,0026
Household characteristics				
2nd quintile	0.0488	0.2362	0.0466	0,2628

3rd quintile	0.0529	0.2282	0.0505	0,2537
4th quintile	0.1367	0.0052	0.1368	0.0055
Richest	0.2780	<0.0001	0.2809	<0.0001
Head with primary education	-0.4316	<0.0001	-0.4322	<0.0001
Head with secondary education	-0.4396	<0.0001	-0.4449	<0.0001
Head with tertiary education	-0.0269	0.8537	-0.0545	0.7062
Age of the head	-0.0110	<0.0001	-0.0113	<0.0001
Head agro-wage earner	-0.2809	0.0370	-0.3055	0.0239
Head non agro-independent	-0.0161	0.7371	-0.0206	0.6698
Head non agro-wage earner	-0.0433	0.3688	-0.0466	0.3372
Head unemployed	-0.1615	0.0163	-0.1644	0.0152
Head at home	-0.0114	0.8329	-0.0168	0.7570
Head student	0.0544	0.8792	0.1414	0.7050
Head inactive	0.2632	<0.0001	0.2623	<0.0001
α parameters				
Intercept			-0.9369	<0.0001
Female			2.0509	0.4926
Urban			2.074	0.3702
LM			21.082	<0.0001

Source: Own computations using 2000 Cape Verdean population census. *Note:* The model explains non-disability.

Table 18: Predicted percentages of disabled persons using misclassification error model estimates

In %	Urban			Rural		
	All	Male	Female	All	Male	Female
15-24 years	2.27	2.90	1.67	4.25	5.28	3.16
25-34 years	3.17	3.70	2.65	5.71	6.26	5.19
35-44 years	4.16	4.61	3.72	8.02	8.97	7.34
45-54 years	8.69	9.06	8.38	14.05	16.48	12.84
55-64 years	17.84	18.11	17.65	22.52	26.13	20.39

Source: Own computations using 2000 Cape Verdean population census.

Table 19: Decomposition of employment gap using misclassification error model estimates

	All			Male			Female		
	Gap	Explained	Residuals	Gap	Explained	Residuals	Gap	Explained	Residuals
All Ages									
Pooled Regression	0.35	0.06	0.29	0.41	0.07	0.34	0.30	0.05	0.25
Disabled Only		0.16	0.19		0.20	0.21		0.15	0.15
Non-Disabled Only		0.00	0.35		0.00	0.41		-0.01	0.31
15-24 years									
Pooled Regression	0.20	-0.02	0.22	0.26	-0.01	0.27	0.14	0.00	0.14
Disabled Only		0.06	0.14		0.05	0.21		0.09	0.05
Non-Disabled Only		-0.04	0.24		-0.03	0.29		-0.02	0.16
25-34 years									
Pooled Regression	0.41	0.07	0.34	0.48	0.10	0.39	0.34	0.06	0.29
Disabled Only		0.18	0.23		0.22	0.26		0.16	0.18
Non-Disabled Only		0.04	0.37		0.06	0.42		0.03	0.31
35-44 years									
Pooled Regression	0.44	0.13	0.31	0.50	0.19	0.31	0.39	0.09	0.30
Disabled Only		0.24	0.20		0.34	0.17		0.18	0.21
Non-Disabled Only		0.07	0.37		0.12	0.39		0.04	0.35
45-54 years									
Pooled Regression	0.45	0.22	0.24	0.56	0.39	0.17	0.39	0.12	0.26
Disabled Only		0.29	0.17		0.45	0.11		0.19	0.19
Non-Disabled Only		0.08	0.38		0.26	0.30		0.01	0.37
55-64 years									
Pooled Regression	0.43	0.25	0.17	0.58	0.50	0.08	0.34	0.11	0.23
Disabled Only		0.30	0.12		0.54	0.04		0.16	0.18
Non-Disabled Only		0.10	0.33		0.45	0.13		-0.06	0.40

Source: Own computations using 2000 Cape Verdean population census.