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Measuring Welfare for Small but Vulnerable Groups: Poverty and Disability in Uganda

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When vulnerable population groups are numerically small — as is often the case — obtaining representative welfare estimates from non-purposive sample surveys becomes an issue. Building on a method developed by Elbers et al., it is shown how, for census years, estimates of consumption poverty for small vulnerable populations can be derived by combining sample survey and population census information. The approach is illustrated for Uganda, for which poverty amongst households with disabled heads is determined.

1. Introduction

Absence of statistically precise poverty information affects many vulnerable groups. Poverty statistics for people with disabilities, for child-headed households, for young widows, for those working in hazardous occupations or for small ethnic minorities, are virtually non-existent. One reason for this paucity of information is that it is hard to obtain representative statistics for small population groups. National sample surveys may collect some information, but typically the number of observations is too small for welfare estimates to be precise. Stratification allows, at least in theory, to identify less populous population groups in sufficiently large

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numbers to provide representative estimates. But in practice stratification of small target populations tends to be dropped in favour of other concerns. Consequently, sample surveys — the main source of information on household welfare for developing countries — provide little (or statistically imprecise) information for small target populations. This leads to a statistical invisibility of the welfare conditions of many less populous groups.

By reporting on each individual in a country, censuses provide precise information for even the smallest population group, but only collect information about non-consumption dimensions of welfare, such as household size, educational attainment or access to clean water. Consequently information about, say, the educational attainment of disabled people is available, but a comparison of the incidence of consumption poverty amongst people with disabilities and the general population cannot be made. In this paper it is shown how small area welfare estimation techniques which combine consumption-based welfare information from national sample surveys with welfare correlates from censuses can be used to generate consumption poverty estimates for small target populations.[2]

There are various approaches to small area estimation (for surveys, see Ghosh and Rao, 1994; Rao, 1999). A method that recently has attracted considerable attention — for its ability to arrive at welfare estimates *and* their standard errors — is described in Elbers *et al.* (2003). It has, to date, only been used to derive welfare estimates for small administrative areas. In this paper the same method is employed to arrive at welfare estimates for small target populations. If these target populations are characterised by limited resilience to avoid poverty and few opportunities to escape chronic poverty, they are often referred to as vulnerable groups.[3] The small vulnerable group on which this paper focuses are people with disabilities.

[2] In the literature the terms 'small area welfare estimation' and 'poverty mapping' are used interchangeably to refer to welfare estimates derived for small target populations.

[3] The term 'vulnerable group' is used even if risk and its consequences for future well-being (that is vulnerability) are less of a concern. Often, however, there is a considerable overlap between vulnerable groups and vulnerability, as limited resilience and opportunities will make vulnerable groups especially liable to further impoverishment in risky environments. For a more elaborate discussion of the distinction between vulnerability and vulnerable groups, see Hoogeveen *et al.* (2004) and the introduction to this volume.

The likelihood that disabled people experience poverty is greater than that for the population at large. There are many reasons for this. Exclusion and discrimination, unequal access to food, health care and education, and reduced capabilities for work all contribute to reduce opportunities for disabled people and their consumption-generating capabilities. Despite the obvious relationship between disability and poverty, there is little to no reliable statistical information to substantiate this point (Metts, 2000; Yeo and Moore, 2003).

Using the Elbers *et al.* (2003) method, poverty estimates are derived, for 1992, for urban Ugandan households with a disabled head. The estimates show that 27% of the urban dwellers are poor and that poverty amongst those who live in a household with a disabled head is much higher, 43%. This latter estimate is argued to be a lower bound. The standard errors of the estimates of poverty incidence amongst people with disabilities are small and lower than the standard errors associated to the poverty estimates obtained from the national household survey. Further disaggregation is therefore feasible and regional estimates of poverty amongst (non)disabled male and female headed households are presented as well.

The paper is organised as follows. In the next section an overview of the available information on poverty and disability in Uganda is provided. This information comprises qualitative data on poverty amongst people with disabilities and quantitative information on household characteristics of disabled people. In section three the estimation strategy to arrive at poverty estimates is outlined and it is explained how the precision of the census-based welfare estimates depends on the size of the target population. Section four briefly describes the data after which section five presents welfare estimates for urban households with a disabled head. Section six discusses for which administrative level precise poverty statistics for people with disabilities can be generated, and presents regional poverty predictions by gender and disability status. Section seven discusses a key assumption underlying the approach: that the prediction model derived for the population as a whole is unbiased for the sub-group of disabled people. It is argued that because the models used for consumption prediction comprise mostly consumption correlates rather than structural variables, prediction bias is less of an issue. The section suggests two approaches to explore the presence of such bias and argues that in the case of disability unobserved household characteristics are likely to lead to an underestimation of poverty. A summary of the findings concludes the paper.

2. Poverty and Disability in Uganda

That Uganda's disabled are deprived is demonstrated in detail by qualitative research. Uganda's Participatory Poverty Assessment (Republic of Uganda, 2002), which operated in 60 sites and 12 of Uganda's 56 districts, provides numerous illustrations of the hardships faced by people with disabilities. Drawing on participatory methods employed in 24 communities, Lwanga-Ntale (2003) shows that the currently disabled are more likely to be poor and that their poverty is passed on to their children. Some quantitative information is available as well. National household surveys administered in 1992 (IHS), 1999/2000 (UNHS I) and 2002/2003 (UNHS II) identify disability as a reason for not attending school.[4] As these surveys include consumption modules from which poverty statistics can be derived, they are a potential source of information on poverty and disability. However, the proportion of respondents who indicated disability as the reason for not going to school is tiny (0.26% in 1999/2000; 0.18% in 2002/2003), and too small to carry out further analysis.

The 1991 population census also asked questions about disability, but only in its long form, which was administered to all urban households and a fraction of the rural households. It is possibly Uganda's richest source of representative quantitative information on people with disabilities. But apart from work done by Okidi and Mugambe (2002), who show that educational attainment amongst disabled people is worse than that for the population at large, this source of information has been little utilised.

Table 1 presents a more detailed, census-based overview of variables associated with the head of household being disabled. Disability is thereby defined in accordance with the Ugandan census manual, which defines disability as any condition which prevents a person from living a normal social and working life. A head of household is considered disabled if this prevents him or

[4] A direct question on the disability status of the respondents is not included.

Table 1: *Census-based Welfare Indicators by Disability Status of Household Head, 1991, Urban Households Only*

	Head disabled	Head not disabled
Percentage of households	5.2	94.8
Age of head	37.6	34.7
Years of education	6.2	7.6
Head of household literate (%)	71	79
Household size	4.7	3.9
Female headed (%)	45	32
Martital status (%)		
Never married	12	18
Married	67	69
Widowed	10	6
Divorced	3	2
Separated	7	5
Number of rooms	2.3	2.2
Number of rooms per adult equivalent	0.5	0.6
Roof material (%)		
Iron	64	63
Other	36	37
Wall material (%)		
Mud	57	47
Cement	10	14
Unburnt brick	17	11
Burnt brick	13	21
Other	3	8
Floor material (%)		
Mud	60	48
Cement	38	47
Other	2	5
Type of tenure (%)		
Owner	39	28
Normal rent	49	50
Other	12	22
Fuel used for cooking (%)		
Electricity	2	4
Charcoal	43	54
Wood	54	35
Other	2	6
Tap water	22	33

(*continued on next page*)

Table 1 (*continued*)

	Head disabled	Head not disabled
Toilet facility (%)		
Flush	7	14
Pit	82	76
Other	12	11
Qualifications of head of household (%)		
None	81	71
School certificate	9	13
Professional certificate	6	8
Diploma	2	3
Degree	1	2
Other	0	0
Education deficit[a]		
At age 12	1.1	0.9
At age 18	2.2	1.9
Main source of livelihood of household (%)		
Subsistence farming	27	12
Petty trade	25	15
Formal trade	4	5
Cottage industry	7	1
Property income	2	2
Employee income	21	45
Other	14	19

Author's calculations using the 1991 population census. The number of urban households with a disabled head is 22165. The number of urban households without a disabled head equals 425333.
[a] Education deficit is defined as (age – 6) – number of years of education received.

her from being actively engaged in labour activities during the past week.[5] Table 1 only comprises information for urban households (information on disability was only collected for a small fraction of the rural households) and does not report standard errors. The reason for the latter is that the information is based on the

[5] *The International Classification of Functioning* (ICF; WHO, 2001) defines disability as the outcome of the interaction between a person with an impairment and the environmental and attitudinal barriers he/she may face. The ICF conceptual framework provides standardised concepts and terminology that can be used in disability measurement. Guidelines on how to measure disability have not been agreed upon. Definitions therefore vary from study to study.

census, so there are no standard errors — at least none attributable to sample design. The descriptive statistics show that approximately 5% of the households are headed by a disabled person and that households headed by a person with disabilities are larger (4.7 versus 3.9 members). Disabled heads are somewhat older (38 versus 35), received less education (6.2 years as opposed to 7.6) and are more likely to be illiterate (29 versus 21%) and female (45 versus 32%). In terms of marital status there is little distinction between disabled and nondisabled heads, except for the fact that disabled heads are less likely to have never married (12 versus 18%) and are more likely to be widowed (10 versus 6%). This may be a reflection of disabled heads being older.

Turning to housing conditions, households headed by a disabled person live in slightly larger houses (2.3 versus 2.2 rooms), though on a per capita basis housing space is smaller for households headed by a disabled person. The quality of housing occupied by households with a disabled head is less. Though there is no difference in the type of roofing material used, walls are more likely to be made of low-quality materials like mud (57 versus 47%) and unburnt brick (17 versus 11%) rather than of cement (10 versus 14%) and burnt brick (13 versus 21%). Also, compared with nondisabled households, floors in disabled households are more likely to be made of mud (60 versus 48%) and less likely to consist of cement (38 versus 47%). Households with a disabled head have less access to tap water (22 versus 33%) and flush toilets (7 versus 14%), and are more inclined to use wood as fuel for cooking (54 versus 35%). Fifty-four per cent of the nondisabled households use charcoal as the preferred fuel for cooking as opposed to 43% of the households with a disabled head. Remarkably, 39% of disabled households own their house, as opposed to 28% of the households with a nondisabled head. Putting together the various pieces of information, it appears that disabled households live in lower quality housing located in the urban outskirts where access to firewood is easier, tap water is less readily available and it is easier to construct one's own home.

That circumstances are worse in households headed by a disabled person is illustrated by housing conditions, but also by the education deficit, which reflects the difference between the number of years a child should have been educated (according to its age) and the actual years of education received. Children in households headed by a disabled head receive less education. To the extent that education drives the ability to earn an income in the future, it confirms quantitatively the qualitative point made by Lwanga-Ntale (2003) that the currently disabled are more likely to pass their poverty on to their children.

Considering the main sources of income, disabled people participate less in the labour market than nondisabled people and are more likely to be self-employed. Whereas employee income is the most frequently mentioned income source (45%) amongst nondisabled households, the most frequently mentioned sources of income for disabled households are subsistence farming (27%) and petty trade (25%). Amongst people with disabilities, employee income is only the third most important (21%) source of income.

3. Methodology

Whereas the information in Table 1 is informative about the non-consumption dimensions of poverty of households with a disabled head — and suggestive of poverty being higher, it does not provide actual information about the incidence of consumption poverty amongst disabled people. This section presents a methodology to derive census-based consumption poverty estimates for people with disabilities. The methodology used here was first described by Hentschel *et al.* (2000) and has been refined by Elbers *et al.* (2002, 2003). Briefly, it comprises regressing household survey per capita consumption on a set of control variables that are common to the survey and the census. Out of sample prediction on unit record census data is then used to yield predicted per capita consumption for each household. Instead of calculating one prediction for each household, a number of simulations (typically 100) are run in which the coefficient vector is perturbed and errors are attributed to the predicted per capita consumption. This yields (100) per capita consumption predictions for each household. By splitting the census data into households with and without a disabled head point estimates of various poverty indicators and their standard errors can be calculated for each group.

Below a more in-depth overview of the method is presented. It is based in part on Elbers *et al.* (2003) and Okiira Okwi *et al.* (2003).

3.1 Deriving Welfare Estimators for Small Target Populations

For a household h in location c the (natural logarithm of) household per capita consumption, $\ln y_{ch}$, can be written as the expected value of per capita consumption conditional on a set of household characteristics, X_{ch}, that are common to both the survey and the census, and an error term ν_{ch}. X_{ch} does not comprise household specific information on disability as this is unavailable in the sample survey.[6]

$$\mathrm{Ln}\, y_{ch} = E[\mathrm{Ln}\, y_{ch}|X_{ch}] + v_{ch}. \tag{1}$$

If there are more households within one location — as is common for household surveys and applicable to the survey used in this paper — the error term can be thought to consist of a location component, η_c, and an idiosyncratic household component, ε_{ch}, and can be written as: $\nu_{ch} = \eta_c + \varepsilon_{ch}$. Using a linear approximation to the conditional expectation in (1), the household's logarithmic per capita expenditure can then be modelled as:

$$\mathrm{Ln}\, y_{ch} = X_{ch}^T \beta + \eta_c + \varepsilon_{ch}, \tag{2}$$

which is estimated using Generalised Least Squares, thus allowing for heteroskedasticity in ε_{ch}.[7,8] In order to do so, a logistic model is estimated of the variance of ε_{ch} with a set of variables z_{ch} as regressors, comprising $\hat{y}_{ch}$, X_{ch}, their squares and all potential interactions.

The log of the variance is rewritten such that its prediction is bound between 0 and a maximum A, set equal to $1.05 \times \max(\varepsilon_{ch}^2)$:

[6] X_{ch} may, however, comprise disability information obtainable from the census that can be included in the survey, such as the fraction of disabled households in the enumeration area or its interactions with household characteristics.

[7] To allow maximum flexibility different models are estimated for each stratum of the national household survey. For this paper four models were estimated, for respectively the Central, Eastern, Northern and Western regions. Table 6 presents, for illustrative purposes, the model derived for the Northern region. The regression models are not very informative by themselves as they only comprise those welfare correlates that work 'best" in explaining per capita consumption and do not have a causal interpretation.

[8] In theory it is possible to also allow for heterogeneity in $\hat{\eta}_c$. In practice the number of observations is too small to do so (namely the number of clusters in the stratum).

$$\mathrm{Ln}\left(\frac{\varepsilon_{ch}^2}{A-\varepsilon_{ch}^2}\right) = z_{ch}^T\alpha + \rho_{ch}. \tag{3}$$

Estimation of (2) and (3) yields the coefficient vectors $\hat{\alpha}$ and $\hat{\beta}$. In combination with household characteristics X_{ch} from the census a prediction of the log consumption for each household in the census, $\ln \hat{y}_h$, can be made. The accuracy of this predicted per capita consumption depends on the properties of the regression model, and especially on the precision of the model's coefficients and its explanatory power. As the interest is in the welfare estimates *and* their standard error, a number of predictions is generated by drawing a set of $\tilde{\beta}$ coefficients along with location and idiosyncratic disturbances. The $\tilde{\beta}$ coefficients are drawn from the multivariate normal distributions described by their respective point estimates, $\hat{\beta}$, and the associated variance covariance matrix. The idiosyncratic error term, $\tilde{\varepsilon}_{ch}$, is drawn from a household-specific normal[9] distribution with variance $\tilde{\sigma}_{\varepsilon,ch}^2$ which is derived by combining the $\hat{\alpha}$ coefficients with the census data.[10] The location error term, $\tilde{\eta}_c$, is drawn from a normal distribution with variance $\tilde{\sigma}_\eta^2$, which itself is drawn from a gamma distribution defined so as to have mean $\hat{\sigma}_\eta^2$ and variance $V(\hat{\sigma}_\eta^2)$. The drawn coefficients $\tilde{\beta}$, $\tilde{\eta}_c$ and $\tilde{\varepsilon}_{ch}$ are used to arrive at the simulated predicted per capita expenditure:

$$\mathrm{Ln}\,\tilde{y}_{ch} = X_{ch}^T\tilde{\beta} + \tilde{\eta}_c + \tilde{\varepsilon}_{ch}. \tag{4}$$

By repeating this process — typically 100 times — a full set of simulated household per capita expenditures is derived.

Welfare estimates are based on individuals rather than on households, and this has to be accounted for. If household h has m_h family members, then the welfare measure can be written as $W(m, y_h, u)$, where m is the vector of household sizes, y_h is household per capita expenditure and u is a vector of disturbances. Disturbances for households in the target population are unknown by definition and cannot be determined. What can be determined is

[9] Emwanu, Okiira Okwi and Hoogeveen, who derived the initial set of census-based poverty estimates for Uganda experimented with various t and non-parametric distributions, and found that the results are robust to the choice of distribution.

[10] Letting $\exp(z_{ch}^T\hat{\alpha}) = B$ and using the delta method, the model implies a household specific variance estimator of $\hat{\sigma}_{\varepsilon,ch}^2 = \left(\frac{AB}{1+B}\right) + \frac{1}{2}Var(\rho)\left(\frac{AB(1-B)}{(1+B)^3}\right)$.

the expected value of the welfare indicators given household size and the census-based predicted household per capita expenditure. After defining an indicator variable, d, taking the value 1 if the head of household is disabled and 0 otherwise, the expected value of the welfare indicator can be denoted as:

$$\tilde{\mu}_d = E[W_d | m, \tilde{y}_h, d]. \tag{5}$$

Based on (5), welfare measures (and their standard errors) can be calculated for households with and without a disabled head. The variable d may take more than two distinct values and could also reflect the location of the household. This is the more conventional approach in small area welfare estimation, yet the possibilities for disaggregation are not limited to disability status or location. Estimates may be disaggregated by any household characteristic obtainable from the census, including household size, educational attainment, age of head of household, occupation, ethnic background or gender, making it possible to generate highly disaggregated census-based poverty profiles.

The performance of these census-based welfare estimators may be judged by their ability to replicate the sample survey's welfare estimates (at the lowest level of representative disaggregation attainable) and the size of the standard error of the census-based welfare estimators for smaller target populations. The prediction error depends mostly on the accuracy with which the model's coefficients have been estimated (model error) and the explanatory power of the expenditure model (idiosyncratic error).[11] Determined by the properties of the expenditure model and the sensitivity of the welfare estimator to deviations in expenditure, the variance attributable to model error is independent of the size of the target population. The variance due to idiosyncratic error falls approximately proportionately in the number of households in the target population (Elbers *et al.*, 2003). That is, the smaller the target population, the greater is this component of the prediction error. This puts a limit to the degree of disaggregation feasible. There is also a limit to which aggregation will increase precision. As location is related to household consumption, it is plausible that some of the effect of location remains unexplained even with a rich set of household specific regressors. The greater

[11] Simulation introduces another source of error in the process: computational error. Its magnitude depends on the method of computation and the number of repetitions. With sufficient resources it can be made as small as desired.

the fraction of the total disturbance that can be attributed to a common location component the less one benefits in precision from aggregating over more households.

4. Data

Two data sets are used to arrive at small area welfare estimates for Uganda: unit record data from the population census and information from the Integrated Household Survey (IHS). The Population and Housing Census was administered in January 1991, covering 450,000 urban households and 3.0 million rural households. It comprised, for all household members, information on household composition, ethnic background, marital status and educational attainment. For urban households a 'long' form was administered which collected additional information on activity status, housing conditions, types of fuel used and sources of water. Based on the responses given on the previous week's activity status, it determined whether a head of household was disabled.

The IHS was administered between January and December 1992, and is of the World Bank's Living Standards Measurement Study type. It is representative at the regional level (Central, East, North and West) for urban and rural areas, and has been used as basis for Uganda's official poverty lines and statistics (Appleton, 2001).

Table 2 presents poverty estimates based on these sources of information. It shows the Foster–Greer–Torbecke measures (FGT(α)), with α-values of 0, 1 and 2 reflecting respectively poverty incidence, the poverty gap and its square. Three sets of poverty estimates are presented: the official poverty statistics derived from the IHS alone, census-based estimates derived after combining census and survey data (taken from Okiira Okwi *et al.*, 2003), and a set of estimates generated after interacting the original census-based model with the fraction of disabled households in each enumeration area. The latter estimates are preferred because they exploit the available disability information from the census.[12] The table shows that the point estimates are not identical, but a t-test does not reject the equality of IHS and census-based poverty estimates at

[12] There may be interest in the poverty estimates derived from the original census model. These are presented in Table A1. The predictions from both models are highly comparable, the main difference being that the standard errors on the disability model are somewhat larger.

Table 2: *Estimates (1992) of Urban Poverty*

		Poverty			Poverty gap			Poverty gap squared		
	Poverty line	IHS	Census based	Disab. model	IHS	Census based	Disab. model	IHS	Census based	Disab. model
Central	17,314	21.0	19.2	19.7	5.8	4.6	4.9	2.2	1.7	1.8
		(3.1)	(1.5)	(1.7)	(1.0)	(0.5)	(0.6)	(0.4)	(0.2)	(0.3)
East	16,548	39.8	38.3	38.5	12.3	13.6	15.2	5.3	6.6	8.5
		(4.0)	(1.1)	(1.9)	(1.9)	(0.6)	(1.9)	(1.0)	(0.4)	(1.7)
North	16,304	49.4	49.6	52.2	19.0	17.2	19.0	9.8	8.1	9.3
		(5.4)	(2.0)	(2.0)	(2.7)	(1.1)	(1.5)	(1.7)	(0.7)	(1.2)
West	16,174	32.8	32.0	34.9	8.8	9.5	10.5	3.6	4.1	4.5
		(3.5)	(1.6)	(1.7)	(1.6)	(0.7)	(0.9)	(1.0)	(0.4)	(0.5)

Standard errors are in parentheses. The IHS and census-based estimates are from Okiira Okwi *et al.* (2003). The estimates for the disability model are derived after interacting all variables of the census-based model with the fraction of disabled households in the primary sampling unit, and maintaining those interacted variables in the model that were significant at the 95% confidence level while keeping all variables from the census-based model. The poverty lines are from Appleton (2001). They are expressed in 1989 shillings.

the 95% level of significance. In other words, once it is taken into account that poverty estimates are associated with a standard error, it is not possible to distinguish the survey- and census-based poverty estimates. In the remainder of the paper the census-based predictions of the disability model are used to obtain poverty estimates for disabled and nondisabled households.

5. Poverty amongst People with Disabilities

Section 3 has shown that reporting consumption poverty for a less populous vulnerable group such as people with disabilities should be feasible if disability is recorded in the census. Such poverty estimates for those who live in a household with a disabled head are presented below. It is believed that assessing the poverty status of households with a disabled head is most revealing as the head of household is typically one of the main breadwinners. Note that estimates on intra-household differences in poverty between disabled and nondisabled household members are not presented. As the welfare estimates are based on per capita household consumption, it is not possible to report such differences. Nor are estimates presented on poverty amongst those who live in households where a person other than the head of household is disabled.[13]

Table 3 presents the number of people living in households with and without a disabled head along with mean per capita consumption and various poverty measures. On average, 5% of the urbanites live in a household with a disabled head, but this figure hides substantial regional variation. The largest percentage of individuals living in a household with disabled head is found in Northern Uganda, 14%. The smallest percentage, 3%, is reported for Central Uganda, the most urbanised region of the country and home to Kampala, Uganda's capital city.

With respect to poverty, the percentage of urban dwellers who stay in a household with a disabled head and who live in poverty is considerably larger than that for those who stay with a nondisabled

[13] This suggests another application: identifying the welfare consequences of the presence of disabled dependents in the household. Households in which a disabled person is present may, ceteris paribus, earn less income because disabled people are likely to earn less, or because others need to forego income to care for the disabled person.

Table 3: *Welfare of Urban Dwellers Living in Households With and Without a Disabled Head, 1992 (Disability Model)*

	Central		East		North		West	
	Disabled	Nondisabled	Disabled	Nondisabled	Disabled	Nondisabled	Disabled	Non disabled
Number of households	8,311	274,556	6,623	69,230	4,505	33,645	2,726	47,902
Number of individuals	37,403	1,057,253	30,111	274,679	22,083	136,900	12,151	183,177
Percentage of individuals	3.4	96.6	9.9	90.1	13.9	86.1	6.2	94.8
Consumption per capita	29,836	34,540	26,180	33,415	19,978	22,072	21,633	25,968
	(1,608)	(1,066)	(2,712)	(4,009)	(4,385)	(4,445.4)	(3,651)	(717)
Poverty	27.9	19.4	48.3	37.4	58.6	51.2	46.7	34.1
	(3.6)	(1.7)	(2.6)	(1.9)	(2.1)	(2.1)	(3.4)	(1.7)
Poverty gap	7.8	4.8	19.2	14.8	22.2	18.5	14.7	10.2
	(1.7)	(0.6)	(2.1)	(2.0)	(1.7)	(1.5)	(1.9)	(0.8)
Poverty gap squared	3.2	1.7	10.3	8.3	11.1	9.0	6.5	4.4
	(1.0)	(0.3)	(1.7)	(1.7)	(1.4)	(1.2)	(1.2)	(0.5)

Author's calculations. Standard errors in parentheses. Per capita consumption is expressed in 1989 shillings. The poverty estimates are based on the disability model. Estimates derived from the 'official' poverty mapping model are very comparable — e.g., national poverty rates are 42 and 25% for disabled and nondisabled households, respectively, are associated with somewhat smaller standard errors. These estimates are included in Table A1.

head: 43% as opposed to 27%. In other words, the (population weighted) probability that people who stay in a household with a disabled head live in poverty is 60% higher[14] than that of people who stay in a household with a nondisabled head. There is considerable regional variation in poverty. This holds for disabled and nondisabled households. Amongst those living in households with a disabled head, the level of poverty is highest in the Northern region, at 59% (compared with 51% for nondisabled), and lowest in the Central region, 28% (compared with 19% for nondisabled). Not only is the incidence of poverty worse amongst households with disabled heads, the severity of poverty, as measured by the poverty gap and the poverty gap squared, is greater amongst households headed by disabled persons. This holds across all regions.

Table 4 considers the differences in poverty between households with and without disabled heads in more detail. It presents the percentage difference between the two groups and shows t-test results on the equality of the various poverty indicators.

The results illustrate the plight of people with disabilities. In terms of per capita consumption, consumption amongst households with disabled heads is 14–22% lower than in households with nondisabled heads, depending on the region. Poverty incidence is 15–44% higher in households with disabled heads. And the results for the poverty gap and poverty gap squared show that the depth of poverty is higher amongst disabled people as well. So, not only are households with disabled heads more likely to be poor, but the degree of poverty is greater as well.

The t-tests reported in Table 4 show that the differences in poverty between disabled and nondisabled people are highly significant. In none of the regions is the hypothesis that disabled and nondisabled people have identical means accepted at significance levels of 5% or less; the same holds for almost all other indicators.

6. How Much Can We Disaggregate?

There is likely to be interest in disability statistics at levels of disaggregation below the region, for instance for each district, or for

[14] Calculated as (42.8–26.7)/26.7.

Table 4: *Tests for Differences in Welfare between Disabled and Nondisabled*

	Central	East	North	West
Percentage disabled	3.4	9.9	13.9	6.2
Consumption per capita	− 13.6***	− 21.6*	− 9.4	− 16.7***
Poverty	43.8**	29.1***	14.5***	37.0***
Poverty gap	62.5**	29.7*	20.0*	44.1**
Poverty gap squared	88.2*	24.1	23.3	47.7*

Author's calculations, given as per cent. Differences are determined as $(x_{\text{disabled}} - x_{\text{nondisabled}})/x_{\text{nondisabled}}$. t-tests have as null hypothesis that means are equal and as alternative hypothesis that disabled households are worse off, and assume unequal variances at an individual level.
*Disabled worse off in mean at the 10% level of significance.
**Disabled worse off in mean at the 5% level of significance.
***Disabled worse off in mean at the 1% level of significance.

sub-groups such as households headed by a disabled female. Could such estimates be provided?

As discussed in Section 3, the precision of the small area welfare estimates declines with the degree of disaggregation. This is because the idiosyncratic error component increases as the number of households in the target population falls. For how small a target population estimates can be reported is an empirical matter that has to be judged by what is an acceptable level of statistical precision. As a benchmark, the precision attained in the household survey is taken, and two measures are distinguished: the absolute magnitude of the standard error and its magnitude relative to the point estimate.

Using the IHS and according to the first criterion, the standard error on poverty incidence in the urban areas varies from 3.1% (in the Central region) to 5.4% (in Northern Uganda). The standard errors for the census-based poverty estimates at the stratum level are less than that: they vary from 2.1 to 3.6% amongst people with disabilities (Table 3). For people without disabilities the standard errors are even smaller. These small standard errors suggest that it is worthwhile to explore whether the poverty statistics can also be reported at lower levels of aggregation, for instance at the district level. Comparing district level standard errors obtained for households with disabled heads with the highest standard error from the household survey (5.6%), this threshold is exceeded in 17 of the 38 districts. For households without disabled heads the results are more encouraging. Only in two districts do the standard errors exceed the threshold of 5.6%.

To further investigate whether poverty estimates could be reported at the district level, Figure 1 presents information on the second criterion, the ratio of the standard error to the point estimate. The value of this ratio is represented by the vertical axis, and districts are ranked from lowest to highest along the horizontal axis. The horizontal line in the figure reflects the highest ratio from the survey estimates (i.e., that for the Northern region). If the zone of acceptability is up to this highest ratio from the survey estimates, then it may be concluded that estimating poverty at this level of disaggregation does not result in particularly noisy estimates for the nondisabled (in accordance with the results from the absolute standard errors), but does for people with disabilities. In about 90% of the districts the estimates for nondisabled people are more accurate than the IHS estimate for urban poverty in the Northern region. But for disabled people this is only true in about 60% of the districts. Taking into account that the benchmark fraction of 0.14 is quite noisy itself, it seems most prudent to only report disability estimates at the regional level and not at the district level.

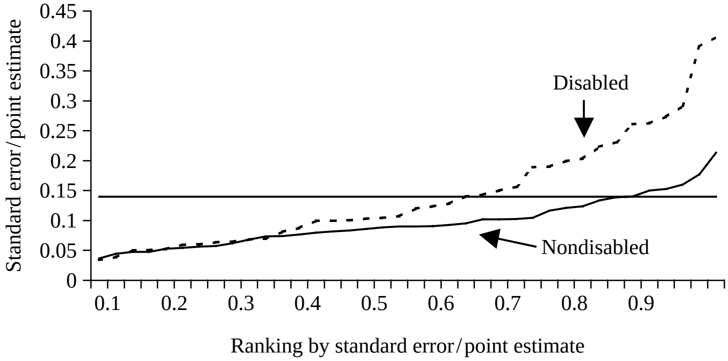

Figure 1: *District Ratios of Standard Error and Poverty Incidence for Disabled and Nondisabled People.*

One reason for the observed increase in standard errors is that in some districts the number of urban households is small — and the number of households with a disabled head is even smaller. Disaggregation into categories that avoid having small numbers in some of the cells is possibly a better approach. For instance, about 31% of the people live in female-headed households. Table 5 shows that such a breakdown by disability status of head of household is indeed feasible, in that the maximum standard error obtained, 4.3%, is considerably less than the highest standard error for the IHS of 5.4%. Yet, few of the differences are significant at the 95% level of significance. This, however, is less a result of the somewhat larger standard errors and more the consequence of the relatively small differences in poverty incidence between male- and female-headed households.

7. Is Poverty amongst People with Disabilities Estimated with Bias?

Consider again the expenditure model presented in Section 3 that is estimated using the survey data:

Table 5: *Poverty by Gender and Disability Status of Head of Household, Urban Households 1992.*

	Nondisabled		Disabled	
	Male	Female	Male	Female
Central	17.9	22.6	25.9	30.9
	(1.6)	(2.0)	(3.6)	(3.9)
East	36.7	39.2	47.6	49.5
	(1.9)	(2.0)	(2.8)	(2.7)
North	52.1	48.9	59.8	56.8
	(2.2)	(2.4)	(2.3)	(2.2)
West	32.4	37.7	43.5	51.9
	(1.7)	(2.6)	(3.5)	(4.3)

Author’s calculations. Standard errors in parentheses.

$$\mathrm{Ln}\, y_{ch} = X_{ch}^{T}\beta + \eta_c + \varepsilon_{ch}. \tag{2}$$

If the sample survey does not collect information on disability, then the welfare correlates of model (2), the *X*-variables, only capture a limited impact of disability, namely that captured by the census-derived means on the fraction of disabled households in an enumeration area (ea) and the interactions of these ea-means with household specific variables.

To the extent that the consequences of disability are captured by the fact that people with disabilities live in houses of lower quality, have lower educational attainment, have less access to tap water, use different sources of fuel and are less likely to work as a paid employee — as Table 1 indicates (i.e., the *X*-variables for people with disabilities differ from those without disabilities) — the model captures their welfare status correctly. The same is true if the consequences of disability are the result of community effects. However, people with disabilities may also differ from those without disabilities in that their βs are different. Stigmatisation and low self-esteem are characteristics of people with disabilities (Yeo and Moore, 2003) that are likely to have systematic consequences for consumption levels. For given levels of education, discrimination in the labour market or physical constraints are likely to lead to returns to education that are different for people with disabilities.

Suppose that one could estimate instead of model (2), an extended model (2^*) which includes interaction terms of *X* with an indicator variable *d* taking the value one if the head of household is disabled and which is zero otherwise:

$$\mathrm{In}\, y_{ch} = X_{ch}^{T}\beta + (dX)_{ch}^{T}\gamma + \eta_c + \varepsilon_{ch}. \tag{2*}$$

If (2^*) is the correct model and the γs are significantly different from zero, then estimating (2) leads to the inclusion of omitted (disability) information in the error term. If, when predicting household consumption from the census, this differential effect is ignored (i.e., the γs are assumed to be zero), predicted consumption will be biased. Which way the bias goes depends on the sign of the γs. If the γs are negative, predicted consumption is too high and poverty is underestimated. If the γs are positive, predicted consumption is too low and poverty is overestimated.

For many small target populations the direction of the bias is hard to determine *a priori*. But in the case of disability it is plausible that the γs are negative, and zero at best. Stigmatisation and low self-esteem are likely to have negative consequences for consumption. Discrimination in the labour market and physical constraints will contribute to a lower correlation of education with consumption. If the assumption that the γs are negative is correct, consumption amongst people with disabilities is overestimated, and the poverty figures presented in Section 5 are a conservative estimate of the true poverty amongst people with disabilities.[15]

Most variables used in the models to predict consumption, however, are correlates of household consumption — type of roof, access to clean water, the type of fuel used — for which there is little reason to assume that their association to consumption is different for disabled and nondisabled people. Only some of the variables in the models are determinants of consumption that may be prone to bias.[16] This can be illustrated with the model for Northern Uganda presented in Table 6. Of the 32 variables, most reflect household composition, the type of housing, the degree to which children missed out on their education or a combination of these. Five of the 32 variables reflect the level of education of different members of the households. Their coefficients could have a more structural interpretation, and could be prone to bias.

Further light on the presence of bias is shed by the six variables that reflect interactions between the fraction of disabled people in an enumeration area and other household characteristics. If there would be bias such that the structural variables of the model do not correctly reflect the βs for disabled people, one expects that the set of variables that presents interactions between the fraction of disabled in a community and other household characteristics would correct for it. One thus expects structural variables to appear prominently amongst these interaction terms. Yet out of

[15] This is reinforced by the fact that who becomes head of household is endogenous. As disability has greater deleterious effects on individual income, it becomes less likely that the individual is in a position to head their own household, possibly leading to the exclusion of the more severely disabled people from the analysis.

[16] The reason for allowing endogenous variables in the model is that the objective is to obtain a set of variables that can give a precise estimate of the expected value of per capita consumption (see also equation 1).

Table 6: *Regression Model for Northern Uganda*.

Variable	Coefficient	t-statistic
Intercept	10.918	81.4
Number of males with secondary education	0.115	3.6
Maximum number of years of education in household	0.022	3.9
Maximum education deficit for those aged 13	0.023	3.4
Log of household size	−0.846	−17.8
Household size is 5	0.157	2.5
Fraction of males aged 50 and over squared	−0.375	−3.6
Number of females aged 25 or less	0.086	5.1
Roof is not made of thatch, asbestos, cement or tiles	−0.190	−3.3
Floor is made of mud	−0.281	−4.4
Household owns the house	0.239	4.8
Tenure is free of charge	−0.188	−3.5
Cooking on charcoal or wood	−0.295	−6.3
Interactions of household variables and enumeration area means (from census)/district dummies		
Head of household married, separated or divorced × Iron roof (ea)	0.428	3.2
Female headed household × District dummy for Nebbi (d)	0.260	2.4
Maximum number of years of education × Lives in house with subsidised rent (ea)	−0.039	−2.4
Mean education deficit at age 13 × Walls made of mud (ea)	−0.085	−2.8
Maximum number of years of education × District dummy for Kitgum (d)	−0.029	−4.9
Maximum number of years of education × District dummy for Nebbi (d)	0.036	3.2
Household size is 9 (ea)	6.483	5.0
Proportion of females aged 6 − 14 (ea)	−3.386	−2.8

(*Continued on next page*)

Table 6 (*continued*)

Variable	Coefficient	t-statistic
Number of males aged 30 and over × Number of Gisu per household (ea)	−3.840	−2.6
Number of males aged 30 and over × District dummy for Lira (d)	−0.174	−2.8
Number of males aged 30 and over × District dummy for Moroto (d)	0.429	3.9
Iron roof × Main source of livelihood is in formal trade (ea)	0.721	2.6
Household has no toilet × District dummy for Gulu (d)	0.488	3.2
Interactions with fraction of disabled heads of household in census enumeration area		
Mean education deficit at age 13 × Number of Gisu per household (ea) × Fraction of disabled (ea)	16.222	3.5
No. of males with secondary education × Hh uses electricity for cooking (ea) × Fraction of disabled (ea)	−262.05	−2.4
Proportion of females aged 30 − 49 squared × Fraction of disabled (ea)	1.862	4.2
Log adult equivalent household size × District dummy for Moyo (d) × Fraction of disabled (ea)	−0.345	−2.5
Number of males aged 30 and over × Hh uses electricity for cooking (ea) × Fraction of disabled (ea)	773.195	4.0
Household has no toilet × Lives in house with subsidised rent × Fraction of disabled (ea)	−32.565	−3.8

The dependent variable is log per capita consumption. (ea) indicates a mean taken for the enumeration area calculated from unit record census data. (d) indicates a district variable. The total number of observations is 658. The adjusted R^2 is 0.64.

the 19 interaction terms included in the model of Table 6, only six comprise interactions with the fraction of disabled people in a community. Out of these six, only one includes a structural variable, namely the number of males with secondary education,[17] and this only in interaction with use of electricity as a source of fuel. The latter is used by only 2% of the population (Table 1). So, when predicting household consumption, this interaction term is relevant for only a very small fraction of the population. This seems to suggests that underestimation of consumption for disabled people due to different βs for structural variables is a limited problem.

A conceptual paper by Van der Weide (2005) suggests ways to further explore whether any of the coefficients are biased. The paper asks what would be the consequences if only one model were estimated and consumption predicted from it, while in fact two models of reality exist (say, one for nondisabled and one for disabled people). It could be that the model that is estimated provides a reasonable description for one section of the population but that a different model applies to the other section of the population. On average, such differences may not be notable, especially when one of the groups is small. If this model is then used to obtain consumption predictions for, say, administrative units, the estimates may be quite reasonable (i.e., the model's predictions of poverty and the survey's prediction would be similar — as is the case in Table 2) and the structural error in the model may go unnoticed. Yet, once disaggregated by group — as is done in this paper — group-based predictions for consumption will be biased.

There are at least two avenues to investigate the presence of such structural error. A first approach does so by estimating a model for enumeration areas rather than for households. In doing so it finds a level of aggregation at which both consumption information (from the survey) and information about disability (from the census) are available. Hence one could estimate:

$$\ln \bar{y}_{ch} = \bar{X}_{ch}^{T}\beta_n + n_{dc}\bar{X}_{dc}^{T}(\beta_d - \beta_n) + \nu_{ch} \tag{6}$$

where n_{dc} measures the fraction of disabled households, d, in enumeration area c, where an upper bar denotes means and where ν_{ch} denotes a zero expectation error term that is uncorrelated with the explanatory variables. Equation (6) could then be estimated by

[17] Another interaction term comprises the education deficit at age 13. Yet this is a consumption correlate, as young children cannot be expected to substantially contribute to household income.

obtaining $\bar{y}_{ch}$ from the survey and the right hand side variables from the census.[18]

Another approach uses an auxiliary model to estimate, in the census, the probability of being disabled. It then takes the predicted probabilities to the survey and estimates:

$$\ln y_{ch} = \begin{cases} X^T_{a,ch}\,\beta_n + \eta_{a,ch} & \textit{with} \quad \textit{probability}\,(1-\pi_d) \\ X^T_{d,ch}\,\beta_d + \eta_{d,ch} & \textit{with} \quad \textit{probability}\,\pi_d \end{cases} \tag{7}$$

where η_{ch} is a zero expectation error term, π_d reflects the probability of being disabled and underscore a refers to nondisabled people. This model could be estimated in a two step procedure. In the first the auxiliary model is estimated (say a logit or probit) from data in the census only. In the second step, the coefficients from the auxiliary model are used to derive estimates of the probability π_d in the survey and to formulate a likelihood function that only has the consumption coefficients as unknown parameters.

The first approach uses information that is readily obtainable from the census and the survey. Whether it can be estimated accurately depends on the loss in information from estimating a model for enumeration areas. In a typical household survey, about 10–20 households are selected from each enumeration area, so this approach leads to a considerable reduction in information. But if there is sufficient variation across the enumeration areas one might be able to estimate equation (6), especially since in a two-type approach there is less need to estimate stratum specific models (as is the case for poverty mapping) so that one gains observations by only estimating one model for the nation as a whole. The success of the second approach depends on the accuracy with which the discrete choice model can predict the probability of being disabled.

For both approaches hold that, apart from estimating correct models, which in and by itself is informative about the accuracy of the estimates, there exist unresolved issues on how to get to consumption predictions. To date, both approaches have been described but not tested empirically. Doing so would not only permit an assessment of the assertion made here — that poverty amongst disabled can be accurately measured using existing

[18] A more efficient way to estimate (6) is to estimate: $\ln y_{ch} = X^T_{ch}\beta_n + n_{dc}\bar{X}^T_{dc}(\beta_d - \beta_n) + \upsilon_{ch}$.

poverty mapping models — it would also allow the focus to be expanded beyond disabled people.[19]

8. Conclusion

Reliable statistics relating to consumption poverty amongst vulnerable groups can potentially go a long way to motivate policy makers to take action. To date, such data have been lacking. One reason for this is that vulnerable groups are typically numerically small. Being less populous, only a limited number of households from the population group of interest are captured in household surveys. And with few observations, accurate poverty numbers cannot be generated, leading to the statistical invisibility of small vulnerable groups.

By combining census with survey data, estimates of consumption poverty can be derived for less populous groups. Provided that information that identifies the small vulnerable group is recorded in the census, it is possible to generate these estimates. Hence poverty statistics for people with disabilities, orphans, child-headed households or ethnic minorities can be generated.

In this paper, the focus is on poverty in households with a disabled head. It has been shown that the numbers support the qualitative evidence on poverty amongst disabled people. In urban areas consumption poverty amongst households with a disabled head is 43%, as opposed to 27% for households with a nondisabled head. The (population weighted) likelihood that people who stay in a household with a disabled head live in poverty is 60% higher than that of people who stay in a household with a nondisabled head.

The estimates presented in this paper are preliminary and may be biased. Depending on the characteristics of the group of interest, the predications may over- or underestimate consumption poverty. An underestimation of poverty occurs if the group of interest has characteristics (unobserved in the survey) that induce it to have lower consumption; poverty will be overestimated if the reverse is the case. A first analysis of whether there is bias suggests that the bias is likely to be small and, if present, is likely to lead to an underestimation of poverty amongst disabled people.

[19] Work in this area is progressing as part a research program funded by the Bank Netherlands Partnership Program.

The estimates are based on information from the 1991 Ugandan Population and Housing Census and the 1992 IHS, and the poverty estimates pertain to this period. This makes the information somewhat dated, especially in view of the large transitions that the Ugandan economy has experienced recently. This is illustrated by the remarkable decline in poverty in the 1990s, from 56% in 1992 to 34% in 1999, and the rise thereafter to 38% in 2002. Such profound changes are likely to have consequences for poverty amongst people with disabilities. In 2002 a new census was implemented, and it is expected that in the near future census-based welfare estimates will become available. These can then be used to create a more up-to-date profile of poverty amongst people with disabilities and to gain experience with the two alternative methods that, if the models can be estimated precisely, would provide unbiased estimates of poverty amongst disabled people.

References

Appleton, S. (2001) 'Changes in Poverty and Inequality 2001', in R. Reinikka and P. Collier (eds), *Uganda's Recovery: The Role of Farms, Firms and Government*, Washington DC: World Bank, Ch. 4.

Elbers, C., J.O. Lanjouw and P. Lanjouw (2002) 'Welfare in Villages and Towns: Micro Level Estimation of Poverty and Inequality', Policy Research Working Paper No. 2911, Washington DC: World Bank.

Elbers, C., J.O. Lanjouw and P. Lanjouw (2003) 'Micro Level Estimation of Poverty and Inequality', *Econometrica*, 71: 355–64.

Ghosh, M. and J.N.K. Rao (1994) 'Small Area Estimation: An Appraisal', *Statistical Science*, 9: 55–93.

Hentschel, J., J.O. Lanjouw, P. Lanjouw and J. Poggi (2000) 'Combining Census and Survey Data to Trace the Spatial Dimensions of Poverty: A Case Study of Ecuador', *World Bank Economic Review*, 14: 147–65.

Hoogeveen J., E. Tesliuc, R. Vakis and S. Dercon (2004) 'A Guide to the Analysis of Risk, Vulnerability and Vulnerable Groups', available at http://wbwebapps5/wwwextweb/sp/risk_management/PDF_files/RVA-V6.pdf.

Lwanga-Ntale, C (2003) 'Chronic Poverty and Disability in Uganda', unpublished manuscript.

Metts, R. (2000) 'Disability Issues, Trends and Recommendations for the World Bank', Social Protection Discussion Paper No. 7, Washington DC: World Bank.

Okidi, J.A. and G.K. Mugambe (2002) 'An Overview of Chronic Poverty and Development Policy in Uganda', Working Paper No. 11, Chronic Poverty Research Centre.

Okiira Okwi, P., T. Emwanu and J.G. Hoogeveen (2003) 'Poverty and Inequality in Uganda: Evidence from Small Area Estimation Techniques', unpublished manuscript.

Rao, J.N.K. (1999) 'Some Recent Advances in Model-based Small Area Estimation', *Survey Methodology*, 25: 175–86.

Republic of Uganda (2002) *Second Participatory Poverty Assessment Process: Deepening the Understanding of Poverty*, Kampala: Ministry of Finance, Planning and Economic Development.

Van der Weide, R. (2005) 'Accurate Assessment of Poverty Among the Disabled', unpublished manuscript.

WHO (2001) *International Classification of Functioning Disability and Health — ICF*, Geneva: World Health Organisation.

Yeo, R. and K. Moore (2003) 'Including Disabled People in Poverty Reduction Work: "Nothing About Us, Without Us"', *World Development*, 31: 571–90.

Appendix

Table A1

Table A1: *Welfare of Urban Dwellers Living in Households with and without a Disabled head, 1992 (Census Model)*

	Central		East		North		West	
	Disabled	Nondisabled	Disabled	Nondisabled	Disabled	Nondisabled	Disabled	Nondisabled
Number	8,311	274,556	6,623	69,230	4,505	33,645	2,726	47,902
Percentage	2.9	97.1	8.7	91.3	11.8	88.2	5.4	94.6
Consumption p.c.	30,694	36,750	22,765	26,914	19,160	21,661	21,269	27,572
	(1,141)	(1,223)	(1,030)	(884)	(955)	(738)	(711)	(733)
Poverty	26.4	18.8	50.4	36.9	56.6	48.4	45.7	31.0
	(2.2)	(1.5)	(1.5)	(1.2)	(2.0)	(2.0)	(2.7)	(1.5)
Poverty gap	6.6	4.5	18.8	13.0	20.6	16.7	14.3	9.2
	(0.8)	(0.5)	(1.0)	(0.7)	(1.3)	(1.1)	(1.3)	(0.7)
Poverty gap squared	2.4	1.6	9.3	6.3	9.9	7.8	6.3	3.9
	(0.4)	(0.2)	(0.7)	(0.5)	(0.9)	(0.7)	(0.8)	(0.4)

Author's calculations. Standard errors in parentheses. Per capita consumption is expressed in 1989 shillings.