Recognizing the Importance of Chronic Disease in Driving Healthcare

Expenditure in Tanzania: Analysis of Panel Data from 1991-2010

Christopher J. Counts¹ & Jolene Skordis-Worrall¹

¹UCL Institute for Global Health, University College London: 30 Guilford Street, London

WC1N 1EH, United Kingdom

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Christopher J Counts; Jolene Skordis-Worrall

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Abstract

Background

Despite the growing chronic disease burden in low- and middle-income countries, there are significant gaps in our understanding of the financial impact of these illnesses on households. As countries make progress towards universal health coverage, specific information is needed about how chronic disease care drives health expenditure over time, and how this spending differs from spending on acute disease care.

Methods

A 19-year panel dataset was constructed using data from the Kagera Health and Development Surveys. Health expenditure was modeled using multilevel regression for three different sub-populations of households: 1) all households that spent on healthcare; 2) households affected by chronic disease; 3) households affected by acute disease. Explanatory variables were identified from a review of the health expenditure literature, and all variables were analyzed descriptively.

Findings

Households affected by chronic disease spent 22% more on healthcare than unaffected households. Catastrophic expenditure and zero expenditure are both common in chronic disease-affected households. Expenditure predictors were different between households affected by chronic disease and those unaffected. Expenditure over time is highly heterogeneous and household-dependent.

Conclusions

The financial burden of healthcare is greater for households affected by chronic disease than those unaffected. Households appear unable to sustain high levels of expenditure over time, likely resulting in both irregular chronic disease treatment and impoverishment. The Tanzanian government's current efforts to develop a National Health Financing Strategy present an important opportunity to prioritize policies that promote the long-term financial protection of households by preventing the catastrophic consequences of chronic disease care payments.

Introduction

The burden of chronic disease is increasing in low- and middle-income countries (LMICs), driven by infectious diseases including HIV and Tuberculosis as well as a growing burden of non-communicable diseases (NCDs). Chronic infectious disease and NCD burdens also compound each other in a variety of ways. First, co-morbidities exist between infectious diseases and NCDs including HIV and cardiovascular disease, and tuberculosis and diabetes (Young *et al.*, 2009). Second, interactions between NCDs, infectious disease, and poverty have been documented; diabetes-affected adults in Tanzania reported the need to make difficult choices between paying for their own care or that of their children with infectious diseases (Kolling *et al.*, 2010).

Existing literature well describes the financial impact of chronic disease in high-income countries, while a small but increasing number of studies has begun to examine this impact in LMICs. Context-specific research is necessary because the financial impact of chronic illnesses is likely to be different in LMIC settings, where health care costs fall more heavily on households and individuals than on governments and insurance schemes (Kankeu *et al.*, 2013). The economic impact of chronic disease on households operates through a combination of direct and indirect costs. Direct costs include both the costs of care itself (consultation, hospitalization, medication, etc.) and the costs associated with accessing care such as the cost of transportation. Indirect costs may be incurred whether or not an individual seeks treatment and consist primarily of lost income due to illness (McIntyre *et al.*, 2006; Kankeu *et al.*, 2013).

A review of studies that examined the household economic burden of HIV/AIDS, TB, and malaria in LMICs found that these illnesses impose regressive cost burdens on patients and their families. Furthermore, costs associated with HIV and TB care were likely to reach a catastrophic level, and poorer households struggled to cope with these costs. A recent study of patient and household TB costs from eight African countries found that pre-diagnostic costs alone often reached catastrophic levels. Despite the value of these cross-sectional analyses examining the economic burden of chronic infectious diseases, there remains a lack of findings drawn from longitudinal data (Russell, 2004; Ukwaja *et al.*, 2012).

A recent review of 49 studies examining the financial impact of chronic diseases (primarily NCDs) in LMICs identified a heavy, regressive financial burden arising from medicine costs and a lack of insurance coverage for NCDs. The review also identified the following substantial gaps in the literature:

- 1. There is little information from the sub-Saharan Africa region;
- Many studies use data collected from individuals identified by convenience sampling, which is likely to bias results and conclusions;
- Few studies compare predictors of expenditure between chronic and acute illnesses;
- 4. There are no analyses of panel data, and a time dimension may be crucial to understanding the evolution expenditure over time (Kankeu *et al.*, 2013).

There is a growing attention to the necessity of financial risk protection for individuals and households, and this protection underpins the movement towards universal health coverage that is on-going in many LMIC settings, including Tanzania (Mtei *et al.*, 2014). Catastrophic out-of-pocket (OOP) health expenditure is a common measure of the impact of a lack of financial risk protection. This data is typically presented as an incidence of households experiencing such expenditure at a point in time (Saksena *et al.*, 2014). Importantly, this indicator—the use of which is necessitated by the cross-sectional nature of many datasets—is unable to signify the impact of catastrophic expenditure on a household over time, further necessitating the inclusion of a time dimension when considering financial risk due to catastrophic health care payments.

Tanzania is a sub-Saharan African country classified as low-income by the World Bank. In 2013 Tanzania's population was 49.3 million, and life expectancy in 2012 was 62 years for females and 60 years for males (World Bank Group, 2013). OOP payments are the primary source of health financing. Available insurance schemes are fragmented, limiting achievable cross-subsidization and risk pooling. Health insurance is, however, mandatory in the formal employment sector, with the National Health Insurance Fund covering public employees and the Social Health Insurance Benefit of the National Social Security fund providing coverage for private sector employees. The Community Health Fund scheme exists for informal sector workers (Mills *et al.*, 2012; Mtei *et al.*, 2014).

In Tanzania, NCDs account for 31% of adult deaths, with cardiovascular disease and diabetes causing 9% and 5% of all deaths respectively. High blood pressure—the leading risk factor for NCDs globally—is also common in Tanzania, affecting 31.6% of male adults and 29.4% of female adults. In 2013, the HIV prevalence rate amongst adults aged 15-49 was 5.0% (UNAIDS, 2013; World Health Organization, 2014).

The data used in this analysis was collected from Kagera, the northwestern region of Tanzania. Approximately half of the population is aged 0-14, and 5% is older than 65 (De Weerdt, 2010). Kagera was an early epicenter of HIV/AIDS, with some of the first cases detected in 1983 originating in this region. The urban area of the Bukoba district was particularly affected, with HIV prevalence peaking at 24% in 1987. Prevalence remained lower in rural areas and decreased across the entire region throughout the 1990s. This study aims to compare the level and predictors of expenditure on health care between chronic disease affected and unaffected households in this region using 19-year panel data.

Methods

Dataset and variable construction

The data used in this analysis comes from the Kagera Health and Development Surveys (KHDS), a longitudinal survey started by the World Bank in 1991. Specifically, 6353 respondents forming roughly 900 households were selected from a stratified random sample of the 1988 census. The sample was stratified on the basis of 1) agroclimatic zone and 2) adult mortality rate (to account for the high prevalence of HIV/AIDS

in this region of Tanzania) (World Bank Development Research Group, 2004). Resurveys of the original respondents were conducted in 2004 and 2010, including tracing of those who had moved out of the region (De Weerdt *et al.*, 2010). This panel had a very low attrition rate compared to other longitudinal surveys, with 93% of original respondents re-contacted in 2004, and 88% re-contacted in 2010 (Litchfield and McGregor, 2008). Appendix 1 contains an in-depth explanation of the survey data and key expenditure variables. Ethical clearance was not required for this study as it is a secondary analysis of publicly available data.

Acute illness was defined as an illness experienced in the four weeks prior to the household interview that lasted less than 6 months; chronic diseases were defined as existing for 6 months or more. Chronic disease therefore can capture both NCDs and other long-run illnesses such as HIV and Tuberculosis. Additional verification questions were asked for each case of illness, including questions regarding the duration, symptoms, and diagnosis of the illness. Examination of self-reported illness perception and practitioner diagnoses for acute and chronic illnesses via tabulation showed that these verification questions resulted in accurate disease classification.

These data are analyzed using longitudinal regression models. Household-level explanatory variables were selected for inclusion on a theoretical basis and from an examination of the health expenditure literature for LMIC settings. Table 4 lists the selected variables, their composition, and descriptive statistics.

Smoking and obesity are two risk factors for chronic disease development and are controlled for with variables that indicate household tobacco expenditure and the number of overweight individuals (Abegunde and Stanciole, 2008).

Total consumption expenditure (TCE) was selected as an indicator of the economic status of households, due to the low levels of formal sector employment in LMIC settings (Deaton, 1997; Howe *et al.*, 2012). TCE and health expenditure are annualized, and health expenditure includes the costs of hospitalization, outpatient care, medicines and transportation. Catastrophic health expenditure was determined by calculating the proportion of the non-food TCE spent on health care, with >40% defined as catastrophic expenditure. This is a commonly used measure as the non-food portion of TCE captures the capacity to pay after meeting subsistence needs, and it has been used in a variety of health expenditure studies in LMICs, including Tanzania (Xu *et al.*, 2003; Chuma and Maina, 2012; Brinda *et al.*, 2014).

The three expenditure-related variables (health expenditure, TCE, and tobacco expenditure) were log-transformed to meet the normality assumption of the multilevel growth model that was fit to the data. There were no zero-value TCE expenditures, and tobacco expenditure data was either non-zero or missing; zero health expenditure values were omitted as missing during log transformation. To minimize truncation caused by the zero health expenditure values, health expenditure was set to missing instead of zero for all households lacking any form of illness. All expenditure variables were adjusted for inflation using a KHDS-specific Fisher price index that corrects prices

both temporally and spatially (World Bank Development Research Group, 2012). Unless otherwise noted, all values are expressed in 2010 USD (1 USD = 1409.27 Tanzanian Shillings) (The World Bank, 2014).

All analyses were done using Stata Version 12. For descriptive analyses comparing health expenditure means, we used the non-parametric Mann-Whitney test to test for statistical significance due to the non-normal distribution of health expenditure.

Regression Modeling

There are several challenges associated with modeling health expenditure. Such data are typically skewed with a right-hand tail, and there are a large number of "zero" value responses from non-spenders. There are also challenges associated with this particular dataset that are not addressed by standard modeling techniques such as two-part models and generalized linear models. First, because the households have repeated measurements for the same variables over time, there is a high degree of autocorrelation between the separate household-level observations in the dataset. Second, the panel is unbalanced; there are uneven gaps in the data (ten years between 1994-2004, and six years between 2004-2010). Finally, household chronic disease presence and the number of disease cases at the household level is not necessarily consistent at all time points in the panel; in other words, households may report chronic disease at one or more time points, but not all time points in the panel.

To address these challenges, a multilevel growth model was selected to examine health expenditure over time. These models incorporate random subject effects (in this case, the subject is the household) to account for the effects of subject characteristics that influence their repeated observations, in addition to a population-level fixed effects specification. We estimated three random effects specifications, which represent 1) individual household variance around the population slope, 2) household variance around the population intercept (together representing between-household variance), and 3) within-household variation. Because time is treated as a continuous independent variable, subjects are not required to have data at every time point, which simultaneously increases statistical power while avoiding bias that would result from the analysis of complete cases only (Hedecker, 2004).

Three different household classifications were used for all analyses: 1) all households with nonzero health expenditure; 2) chronic disease affected (CDA) households; 3) households affected by acute disease, referred to here as chronic disease unaffected (CDU) households.

Results

Descriptive analyses

Across the panel, 31% of households reported one or more cases of chronic disease. In all but two years (1991 and 1993), health expenditure was higher in CDA households compared to CDU households (Table 1). Across all years, mean health expenditure was

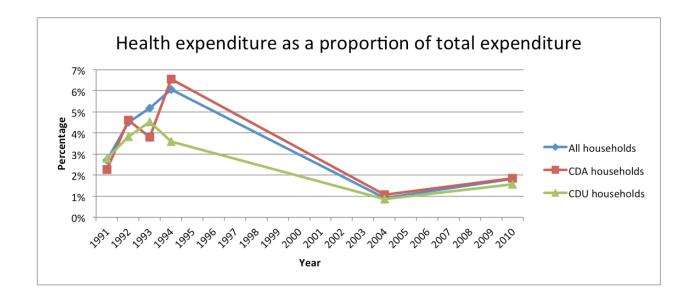
\$39.63 (SD: 287.91) for CDA households and \$32.63 (SD: 255.70) for CDU households (p<0.0001).

Table 1. Mean health expenditure (inflation adjusted and expressed in 2010 USD)

Household	1991	1992	1993	1994	2004	2010
type	(SD)	(SD)	(SD)	(SD)	(SD)	(SD)
All spending	\$39.92	\$42.06	\$60.81	\$66.88	\$13.48	\$38.01
households	(329.46)	(333.64)	(538.78)	(580.39)	(22.71)	(75.66)
Chronic	\$36.18	\$58.78	\$42.44	\$85.42	\$16.12	\$42.69
disease	(54.20)	(542.42)	(171.77)	(647.06)	(22.13)	(102.93)
affected						
households						
Chronic	\$44.83	\$34.63	\$59.79	\$34.30	\$11.91	\$30.76
disease	(396.39)	(153.42)	(536.92)	(81.50)	(18.96)	(45.71)
unaffected						
households						

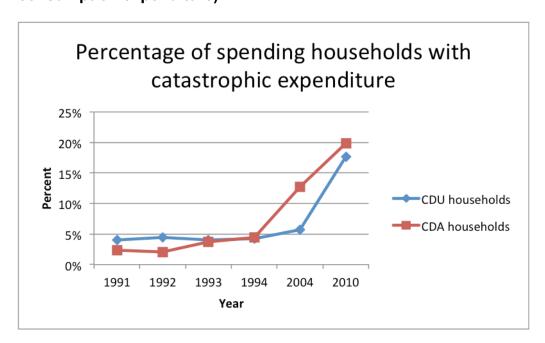
Across the panel, health expenditures represented 2.74% (SD: 0.18) of total consumption expenditure for CDA households, compared to 2.54% (SD: 0.12) in CDU households (p=0.0034). There is a notable decrease in health related spending between years 1994 and 2004, and an increase between 2004 and 2010 (Table 1 & Figure 1).

Figure 1. Health expenditure over the 19-year panel, expressed as a percentage of total consumption expenditure and stratified by household disease status.



From 1991-1994, 3.16% of CDA households spent catastrophically, compared to 4.18% of CDU households. Levels of catastrophic spending increased substantially for both sub-populations of households in 2004 and 2010, although the increase for CDA households was greater (Figure 2). 12.70% and 19.91% of CDA households spent catastrophically in 2004 and 2010, respectively. Across the panel, 7.54% of CDA households spent catastrophically, compared to 6.68% of CDU households.

Figure 2. Rates of catastrophic spending (defined as >40% of non-food consumption expenditure).



Rates of non-spending on health care among CDA households was low during the years 1991-1994 and increased substantially during years 2004 and 2010 (Table 2).

Table 2. Percentage of CDA households with zero health expenditure.

	1991	1992	1993	1994	2004	2010
% of CDA households	0.00%	1.36%	0.62%	1.35%	6.32%	14.76%
with zero health						
expenditure						

The lowest wealth quintile had the highest number of ill individuals, and the lowest rates of health expenditure and catastrophic spending. Quintiles four and five have the highest rates of health and catastrophic spending (see Table 3).

Table 4. Descriptive statistics for household-level health expenditure and independent variables.

Variable	Description	Mean	Std. Dev.	Min	Max
Healthexp	Household level expenditure on health care (expressed in 2010 USD)	34.46	279.10	0	11566.27
ConsumptionExp	Household level consumption expenditure (expressed in 2010 USD)	1457.29	1318.43	25.63	19087.90
Chronic	Number of adults reporting chronic disease	0.38	0.64	0	5
Nonchronic	Number of adults reporting non-chronic disease	0.89	0.92	0	8
Headwork	Household head works (binary)	0.59	0.49	0	1
Headmale	Household head is male (binary)	0.76	0.42	0	1
Headsingle	Household head is unmarried (binary)	0.33	0.47	0	1
HeadAge	Age of the household head	44.27	16.87	16	99
HeadEducation	Years of education of the household head	6.97	2.87	0	21
Tobaccoexp	Household expenditure on tobacco in the past 2 weeks (2010 USD)	0.59	1.25	0.004	20.86
Overweight	Number of overweight individuals (BMI>25)	0.20	0.47	0	5
Size	Household size	5.38	3.12	0	36
Adults	Number of adults in the household	2.28	1.17	0	16
Elderlymen	Number of elderly men older than 65 years	0.09	0.29	0	2
Elderlywomen	Number of elderly women older than 65 years	0.12	0.34	0	3
Insurance	Number of individuals covered by an insurance scheme	0.14	0.49	0	7
Private	Household use of private clinics, including traditional healers (binary)	0.16	0.36	0	1
Urban	Urban location of household (binary)	0.17	0.38	0	1
Education	Average years of schooling of household members	5.75	2.32	0	17
Age	Average age of household members	24.17	11.89	7.25	94

Table 3. Illness, health spending, and catastrophic spending by quintile.

Quintile	n	n with illness	n spenders	% of ill that spend	n catastrophic	% catastrophic
			•	•	spending	spending
1	1853	1411	1243	88%	65	5%
2	1853	1326	1234	93%	74	6%
3	1853	1275	1199	94%	121	10%
4	1853	1245	1203	97%	149	12%
5	1853	1217	1170	96%	163	14%

Regression analyses

Three multilevel growth models were fit to model the predictors of health expenditure in the three populations of households. The first model examines the predictors of health expenditure in the population of households with non-zero health expenditure, regardless of chronic/non-chronic disease status (Table 5). The second model examines predictors of health expenditure among CDA households (Table 6). The third model examines predictors of health expenditure among CDU households (Table 7).

For the population of spending households, time and household size are strong positive predictors of expenditure, while an unmarried household head and increasing household age are strong negative predictors of expenditure. An urban location and a higher number of insured individuals weakly but positively predict expenditure.

Table 5. Regression results for spending households.

logHealthExp	Coefficient	р
Time	0.0192551	0.000
Nonchronic	-0.0041958	0.497
Chronic	-0.0063695	0.470
Headwork	0.012882	0.233
Headmale	-0.035051	0.356
Headsingle	-0.0773257	0.002
HeadAge	0.0014355	0.178
HeadEducation	0.0017139	0.716
logTobaccoexp	-0.0022767	0.695
Overweight	0.0030682	0.831
Size	0.0656502	0.000
Adults	-0.0048474	0.552
Elderlymen	-0.0382192	0.276
Elderlywomen	0.0377922	0.160
Insurance	0.0562016	0.081
Private	-0.023205	0.215
Urban	0.1177726	0.087
logConsExp	0.0149477	0.227
Education	0.0003221	0.959
Age	-0.0027624	0.012
Constant	8.967644 0.0	
Random Ef	fects Specifica	ations
Specification	Value	р
sd(slope)	-2.321	0.000
sd(intercept)	0.376	0.000
sd(household)	-2.392	0.000

N 1,454 Number of groups 804

For the population of CDA households, time is not a significant predictor of expenditure. Household size, the number of adults, and the number of elderly men in a household are strong positive predictors of expenditure, while a male household head and an unmarried household head are strong negative predictors of expenditure. The education level of the household head positively predicts expenditure, while the average

household age negatively predicts spending. Finally, urban location is a weak positive predictor of expenditure, while the number of overweight individuals is a weak negative predictor of expenditure.

Table 6. Regression results for CDA households.

logHealthExp	Coefficient	р
Time	0.0036426	0.561
Chronic	0.0008877	0.941
Nonchronic	-0.0117211	0.167
Headwork	0.0146282	0.203
Headmale	-0.296144	0.002
Headsingle	-0.2859161	0.000
HeadAge	0.000945	0.648
HeadEducation	0.0176821	0.018
logTobaccoexp	0.0032634	0.553
Overweight	-0.023758	0.058
Size	0.0659472	0.000
Adults	0.0243677	0.009
Elderlymen	0.1674903	0.001
Elderlywomen	0.01559	0.546
Insurance	0.03413	0.707
Private	0.0243348	0.143
Urban	0.2361526	0.085
logConsExp	0.002934	0.846
Education	-0.0106249	0.153
Age	-0.003232	0.048
Constant	9.498247	0.000
Random Ef	fects Specifica	ations
Specification	Value	р
sd(slope)	-2.869	0.000
sd(intercept)	0.138	0.000
sd(household)	-3.820	0.000

N 472 Number of groups 372 For the population of CDU households, time was a positive predictor of expenditure; thus, CDA households were the only population for which expenditure does not appear to increase over time. A male household head negatively predicts expenditure while the education level of the head positively predicts expenditure; however, these effects are weaker in CDU households compared to CDA households. In contrast, urban location is a strong predictor of expenditure in these households, while this effect was more modest for CDA households. Finally, household size is a strong positive predictor of expenditure, while the number of insured individuals is a weak negative predictor of expenditure.

Table 7. Regression results for CDU households.

logHealthExp	Coefficient	р	
Time	0.0400550	0.005	
Time	0.0122553	0.035	
Nonchronic	-0.0026051	0.705	
Headwork	0.0110865	0.342	
Headmale	-0.0804274	0.058	
Headsingle	0.0179105	0.496	
HeadAge	0.0012965	0.312	
HeadEducation	0.0089433	0.094	
logTobaccoexp	0.0005803	0.929	
Overweight	0.0185591	0.261	
Size	0.0633386	0.000	
Adults	0.0021816	0.816	
Elderlymen	-0.0443497	0.297	
Elderlywomen	-0.0202822	0.587	
Insurance	-0.0664356	0.058	
Private	-0.0136477	0.523	
Urban	0.2299636	0.017	
logConsExp	0.0035163	0.796	
Education	0.002802	0.702	
Age	-0.0016441	0.186	
Constant	9.092241	0.000	

Random Effects Specifications					
Specification Value p					
sd(slope)	-2.518	0.000			
sd(intercept)	0.325	0.000			
sd(household)	-2.633	0.000			

N 982 Number of groups 623

Finally, the three random-effects specifications were highly significant in all three models, demonstrating considerable variation in both the level of expenditure and the change in expenditure by households over time.

Discussion

The finding that households affected by chronic diseases experience a greater OOP expenditure burden (in this study, 22% higher), confirms other studies from LMIC contexts (Russell, 2004; McIntyre *et al.*, 2006; Chuma *et al.*, 2007). This higher level of expenditure might be explained by the long-term nature of treatment for chronic illness, and also by the fact that most CDA households (73.9%) also experienced one or more instances of acute illness, which suggests that households might spend to meet healthcare needs for several household members. Alternatively, the individual experiencing chronic disease could simultaneously be experiencing an acute (or chronic) comorbidity. The observation that catastrophic expenditure was more common in households within the higher economic quintiles (12% and 14% in the top two quintiles compared to 5% and 6% in the bottom two quintiles) suggests that better-off households tend to spend a larger portion of household resources on health care than

poorer households; this aligns with a finding that was observed in the context of Asian countries (van Doorslaer *et al.*, 2007). Alternatively, poorer households might not seek care due to the direct and indirect costs of care-seeking, which could explain the observation of lower health care expenditure in the bottom two quintiles. The increase in both catastrophic- and zero-expenditure beginning in 2004 remains an important topic for further examination.

Catastrophic expenditure rates for both CDA and CDU households were also higher than the recently reported Tanzanian national average of 2%; this could be a result of the HIV/AIDS burden in the Kagera region, which was substantially larger compared to other parts of Tanzania. (Mtei *et al.*, 2014)

Across the 19-year panel, time was a significant positive predictor of expenditure for CDU households, suggesting a general increase in health care expenditure over time. However, time was not a significant predictor of expenditure for CDA households. This suggests that CDA households are unable to maintain high levels of chronic disease care expenditure over time. An increase in the number of adults in a household reporting chronic or non-chronic illness did not significantly increase health expenditure. This suggests that households might lack the resources to increase health expenditure when there are multiple cases of either chronic or acute disease.

In all three models, urban household location was a positive predictor of expenditure.

This suggests that individuals residing in rural areas might be less likely to receive

treatment. Alternatively, these individuals might be receiving more cost-efficient care from dispensaries or health centers (instead of at costlier hospitals), or care that is subsidized through community-based programs. (Saronga *et al.*, 2014). Among all spending households, the number of household members covered by an insurance scheme positively predicted health expenditure (p=0.081). This aligns with the findings of other studies (Ruger and Kim, 2007; Abegunde and Stanciole, 2008) and suggests that in the Tanzanian context insurance schemes may offer some—but not complete—protection from incurring OOP expenditure. Another possible explanation lies within the earlier observation that increasing cases of illness do not correlate with increasing expenditure. It is therefore possible that the presence of increasing numbers of insured individuals allows households to use financial resources to access care for those not covered by an insurance scheme. An examination of individual-level expenditure and insurance status by household would be necessary to further evaluate this idea.

Demographic characteristics of the household head are more important to predicting health expenditure in CDA households than in CDU households. For example, the presence of a male household head and/or an unmarried head negatively predicts expenditure (p=0.002 & p=0.000), while education level of the head positively predicts expenditure (p=0.018). However, in CDU households, only the male head and education level trends are conserved, and even then only at the p<0.1 level. These results suggest that decisions regarding expenditure might be made differently for chronic versus acute diseases. While the head of the household has previously been identified as playing a key role in determining other household members' access to

health care, it appears that this role might be influenced when the decisions relate to accessing care for a chronic condition (Anderson and Bartkus, 1973; Okunade *et al.*, 2010; Fang *et al.*, 2013).

The number of adults and the number of elderly men in a CDA household are also strong positive predictors of health expenditure, which aligns with the idea that these individuals are more likely to develop a chronic condition (most likely an NCD) and incur health expenditure as a result. Accordingly, these two variables were not significant predictors of expenditure in CDU households.

Although total consumption expenditure is positively associated with health expenditure, this trend was not statistically significant in any of the three models. The economic status of a household has repeatedly been shown to be a significant positive predictor of health expenditure (Andersen and Newman, 1973; Parker and Wong, 1997; Abegunde and Stanciole, 2008; Okunade *et al.*, 2010; Fang *et al.*, 2013). When the log of non-food consumption expenditure was used in place of TCE, this measure of income became a positive predictor of health expenditure with greater statistical significance (not shown). These results suggest that non-food consumption expenditure, which represents a household's capacity to pay, is a better measure of the economic status of a household than TCE for this setting.

Finally, the random effects parameters that estimate between household variance and within household variance represent an important finding of this study. These effects

were highly significant in each of the three models, and indicate that there is a significant degree of household variation around the population-level health expenditure growth curve. Taken together, these results suggest that CDA households—and indeed, all households in Kagera that have nonzero health expenditure—have highly heterogeneous health expenditure patterns over time. Although the fixed effect regression results indicate that these expenditure patterns are determined in part by household characteristics such as size, economic status, urban location, insurance coverage, and demographic characteristics of the household head, these parameters suggest that expenditure patterns are also highly household-specific, especially when considered over an extended period of time.

Finally, Tanzania has several health system characteristics that are common to other LMIC settings. These include a relatively fragmented financing system shaped by a history of colonial rule and structural adjustment, and a high proportion of out-of-pocket payments. (McIntyre *et al.*, 2008) It is therefore likely that the household spending patterns presented here are also relevant to CDA households in similar settings. However, it is also worth noting that this dataset showed higher rates of catastrophic spending (7.54% among CDA households and 6.68% in CDU households) than the Tanzanian national average of 2%, which might be explained in part by the historically high rates of HIV/AIDS in this region of the country. (Mtei *et al.*, 2014)

While every attempt has been made to make best use of the available secondary data, this study has a number of known limitations. First, incurred costs are likely to vary by

chronic disease; medicines tend to be the largest component of treatment costs, and the level to which these costs might be subsidized is likely to vary by disease. For example, this region has experienced significant scale-up in HIV treatment programs; meanwhile, the cost of insulin treatment for diabetes remains significant. Costs of palliative care in sub-Saharan Africa have also been shown to be significant (Harding and Higginson, 2005; Kankeu *et al.*, 2013). The large proportion of individuals lacking a formal diagnosis of their condition (39.2% across the panel) limited the potential to accurately control for the effects of specific diseases. The reported prevalence of chronic disease could also be underestimated due to a reliance on self-reported information; low levels of diagnosis, lack of awareness of disease progression, and stigma surrounding certain illness such as HIV could have limited self-reporting. (Binnendijk *et al.*, 2012; Walker *et al.*, 2013).

The large proportion of zero health expenditure responses results in truncation of the dependent variable, a common challenge in analyzing health expenditure data (Deaton, 1997). However, log transformation of the health expenditure variable was necessary because multilevel growth models rely on a normality assumption that, if violated, produces biased confidence intervals and hypothesis tests (Bernier *et al.*, 2011). There is limited information in the literature regarding the behavior of multilevel growth models under the presence of censoring and truncation (Sweeting and Thompson, 2012). Across this dataset, 4.63% of health expenditure responses were equal to zero, which is low compared to other settings (Okunade *et al.*, 2010). Meanwhile, the annualized nature of the health expenditure data could result in a 'scaling up' of acute expenditure;

this might overestimate levels of health related spending, and should be kept in mind when interpreting this data. Furthermore, the addition of time-varying covariates into the multilevel models might better model any potential lagged effects of chronic disease on household health expenditure, which might better address the endogenous nature of health status to health expenditure (Rous and Hotchkiss, 2003; Hedecker, 2004).

Additional examination of the increasing levels of zero expenditure and catastrophic expenditure over the panel is also warranted.

It is also worth discussing the decrease in health-related expenditure between 1994 and 2004 (Table 1 and Figure 1); we see two possible explanations for this. First, questions regarding health related spending were moved from the health-related section of the survey to the individual expenditure portion of the survey in 2004. The specific wording of the questions was also changed slightly. Second, the decrease could be a reflection of the evolution in the HIV burden that occurred during the gaps between the data collection points in the 1990s and the 2000s. For example, the development of HIV programs providing subsidization of medicines and services between the 1990s and 2010 could explain the relative decrease between these time points, as could the corresponding increase in life expectancy due to ARV availability and an associated decrease in palliative care costs, which are known to be high.

Finally, the dataset lacks information on monetary and/or asset transfers to households that is consistent across all years of the panel; data surrounding household splits resulting from illness-related financial stress are also lacking. Therefore, no conclusions

can be drawn regarding how households might cope with the financial burden of chronic disease. This remains an important topic for future examination.

Conclusion

The results of this study have revealed the financial burden of chronic disease affected households. These households appear unable to sustain high levels of expenditure over time. Predictors of expenditure are highly heterogeneous and household-dependent, and differ between chronic disease affected and unaffected households. Our analysis of the KHDS panel demonstrates the importance of analyzing the financial risk of catastrophic health expenditure with a time dimension. The findings of this study, concurrent with the Tanzanian government's present efforts to develop a health financing strategy, demonstrate the importance of policies that provide long-term financial protection of Tanzanian households experiencing chronic illness.

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Appendix 1: KHDS Survey Data Description

The KHDS survey series includes a comprehensive household questionnaire as well as several additional community questionnaires. Data collected at the household level include information regarding consumption, income, assets, household amenities, business activities, time allocation of individuals, and individual health, education, and anthropometric information. One of the community questionnaires collected detailed food and non-food price information from various local stalls and marketplaces. These were used to construct a KHDS-specific Fisher price index to adjust for inflation across the panel.

The KHDS strategy for the follow-up survey rounds (2004 and 2010) was to track and re-interview individuals rather than households due to the dynamic nature of a household over time. As a result, the first time point contains roughly 900 households, while the 2010 data point represents over 3,300.

Description of key expenditure variables

Total consumption expenditure (TCE) includes:

- food expenditure
- consumption of home production, including food; business outputs; livestock; and any other non-food consumption
- alcohol and cigarette consumption
- consumption of non-food items including rent, tax, clothing, jewelry, fuel, and services

- sent remittances
- expenditure/consumption of wage income that was received in-kind

The components of TCE had recall periods ranging from two weeks to one year depending on the nature of the item. TCE was expressed as an aggregate variable assembled by the KHDS team for download with the rest of the data, and it is expressed as an annualized value adjusted for inflation.

Health expenditure was collected for both living and deceased individuals, and was collected in two different manners for comparison and verification purposes by the KHDS team at the beginning of the panel:

- Section 18A of the survey collected expenditure information for either the past 12 or 6 months in two broad categories: medicines and other medical services.
- 2. Section 6 (the Health section) asked questions that linked spending to episodes of acute illness occurring in the past four weeks, including medicines, hospitalization, outpatient costs, and transportation. There was an additional 'global' question for all expenditure on chronic conditions that occurred in the past four weeks.

When comparing the two methods, there were very few instances (across 1991-1994, less than 3% overall) in which the summed expenditure from Section 6 exceeded that from Section 18 (as would be expected due to the shorter recall period of the questions in Section 6). For those few individuals, annual health expenditure was summed from

Section 6. For the remaining majority of individuals, annual health expenditure was set as the sum of the items in Section 18 plus the transportation costs collected in Section 6A. In a manner similar to the TCE variable, health expenditure was summed for all individuals in a household to arrive at an annual household total. (World Bank Development Research Group, 2004)

Changes in survey structure and implementation across the panel

Below we describe changes that occurred in the survey structure, design, and/or implementation that occurred in the two re-survey rounds of 2004 and 2010. We describe these changes for both TCE and health expenditure, which are the critical expenditure variables used in our analysis. The majority of the changes were global section order and structure changes.

TCE related changes from 1991-1994 to 2004

- In 2004, individual expenditures originally assessed in Section 18B were moved to section 15C and instead assessed at the household level. These included household supplies such as fuel. This original Section 18B was then dropped.
- In 2004, some individual expenditures originally assessed in Section 18A were moved to the Household Annual Expenditure level (Section 15B in 2004)
- In 2004, Section 8 became the Individual Expenditure section. Some of the individual expenditure questions had changes in recall periods and wording.
- In 1991-1994, there was a unique fishing section that in 2004 was moved to the non-farm self-employment section.

- In 2004, crop-related questions were further divided into questions for each specific crop sub-type.
- In 2004, questions regarding income and expenditures for enterprises were combined into the same category (they were in separate categories in 1991-1994).
- In 2004, consumption of home grown fruits and vegetables were combined; in
 1991-1994, data was collected for each item

Health expenditure related changes from 1991-1994 to 2004

- In 2004, health expenditures were assessed only in the Individual Expenditures section instead of in the health section. This Individual Expenditure section was moved to Section 8 from the original Section 18.
- The exact wording of the health related expenditure questions changed slightly in order to capture transportation costs (originally in Section 6, the health section), and the recall period was set at 12 months.

(Beegle et al., 2006)

In 2010, KHDS shifted to an electronic survey collected on handheld computers. Price data, originally a community questionnaire, was collapsed into the household questionnaire.

TCE related changes from 2004 to 2010

- A few individual expenditure items, including expenditures on sports, cinemas, and gambling were dropped.
- Questions surrounding the sale of crops were moved to a new Land section.
- 2004 questions regarding farm inputs were dropped.
- In 2010, detailed questions regarding expenditure and income relating to enterprises were dropped.
- In 2010, household expenditure items were updated (for example, to include a category on mobile phone and internet expenditures).

Health expenditure related changes from 2004 to 2010

 Illness associated expenses for household members who died in the past 12 months were dropped, as were funeral and other death-associated expenses for these members

(De Weerdt *et al.*, 2010)

Full descriptions of survey design and implementation are available in the Basic Information Documents cited above.

Appendix 2: Regression Modeling

First, it is worth noting that there are a variety of methods that can be used to address the challenges of modeling health expenditure data, and there is considerable debate as to which models are best suited for various circumstances (Buntin and Zaslavsky, 2004) Here we describe some limitations to standard two-part models and generalized linear models that we considered while choosing an approach to the model health expenditure data for this panel.

Two-part models separately model 1) the probability of spending on health care and 2) the level of spending conditional on nonzero expenditure (Duan *et al.*, 1983). The second part usually utilizes a transformed expenditure or cost variable that is then retransformed for interpretation. However, a smearing factor must be used in the event that the error term is not normally distributed, and in some cases heteroscedasticity in the error term may still result in the incorrect estimation of expenditure despite application of the smearing factor correction (Duan, 1983; Buntin and Zaslavsky, 2004).

Generalized linear models (GLMs) are another option that use a link function to model the mean and variance on the original scale of the dependent variable (Nelder and Wedderburn, 1972). However, GLMs are more likely to give imprecise estimates in the event of a mean or variance function misspecification, as they have weaker model assumptions when compared to alternatives such as the two part model and OLS regression (Buntin and Zaslavsky, 2004).

The additional challenges associated with this particular dataset that were mentioned in the Methods section (autocorrelation, the unbalanced panel, and inconsistent chronic disease presence), along with the additional insight offered by estimating household-dependent random effects in addition to the population-level fixed effects led us to choose a multilevel regression model (Stata command xtmixed).

Multilevel models are represented by the equations listed below, which also indicate the fixed and random effects specifications:

Level 1 (within-subjects): $y_{it} = b_{0i} + b_{1i} \cdot x_{it} + \varepsilon_{it}$

Level 2 (between-subjects): $b_{0i} = \beta_0 + v_{0i}$

$$b_{1i} = \beta_1 + v_{1i}$$

 y_{it} = dependent variable (the log of health expenditure) for household i at time t

 b_{0i} = individual's intercept (initial level of health expenditure)

 b_{1i} = individual's slope (health expenditure time trend)

 β_0 = population intercept (fixed effect)

 β_1 = population slope (fixed effect)

 v_{0i} = intercept deviation for household i (random effect)

 v_{1i} = slope deviation for household i (random effect)

 x_{it} = independent variable x for household i at time t

 \mathcal{E}_{it} = independent error term with variance σ (Hedecker, 2004).