Today, tomorrow, forever: A Bayesian ordered categories model for treatment seeking in febrile children

Lawrence N. Kazembe[a]*, Isak Neema[a]
[a]Department of Statistics and Population Studies, University of Namibia

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Abstract

Early diagnosis and prompt treatment of febrile conditions is a key strategy towards control of the disease from progressing to severe or fatal stages. In this paper, we studied the timing of treatment among children with a history of diarrhoea and fever in Namibia, while simultaneously investigated socio-economic and spatial factors that influence the treatment seeking behaviour. A multinomial probit model with ordered categories was estimated, and results confirmed that there was significant spatial variation at regional level. Socio-economic factors also explain treatment seeking having controlled for spatial dependence. The spatial variation can be interpreted as representing unobserved heterogeneity not captured by the data or possible clustering inherent in nested survey data.

Keywords: febrile conditions, Namibia, Bayesian, treatment seeking behaviour, ordered categorical models.

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1 Introduction

Children in sub-Saharan Africa experience a disproportionately huge burden of morbidity and mortality. Recent estimates indicate that there are 180 deaths per 1000 live deaths in the region [1], and most of them get ill and die from relatively small number of infectious diseases such as diarrhoea, acute respiratory infection and malaria [2]. In many ways than not, these illnesses occur simultaneously, largely because of common risk factors, and probably due to overlap between multiple risk factors, or that one disorder creates an increased risk for the other [1; 3].

The burden of febrile conditions still remains intolerable in Namibia, in particular, diarrhoea is attributed to 11%, while acute respiratory infections was estimated at 6% with coughing and rapid breathing standing at 5%. Fever, as an indicator of malaria was reported at 17% [4]. In keeping up with the Millennium Development Goals 4 and 5, as well as the Roll Back Malaria initiative and its goals, Namibian Government has adopted the four key strategies of controlling childhood

*Corresponding author; E-mail: lkazembe@unam.na

diseases- through the integrated management of childhood illnesses (IMCI). One such strategies is early diagnosis and prompt treatment with effective treatment [5; 6].

However, the success of this strategy depends upon improved delivery of services on the part of government and an understanding of the disease by the patient or care-givers among other things [6]. In econometrics these are referred to respectively as the supply side and demand side of health care [7; 8]. Health care decisions are influenced by a myriad of factors including individual, household, and community variables. Andersen framework on heath seeking behaviour summarized these factors as predisposing, enabling, and needs factors [9]. These factors in turn are strongly correlated to geographies. Cultural and economic factors vary from place to place. There is a growing recognition of the importance of cultural and social information in disease control, and need to understand socio-economic barriers on treatment seeking behaviour, hence on disease control [5].

The aim of this paper is to investigate treatment seeking behaviour for children presenting with febrile conditions. We study the geographical variability of timing of treatment after the onset of fever/cough and diarrhoea, while we simultaneously investigated important socio-economic variables that influence behaviour, using a national-wide survey data conducted in 2006/2007 in Namibia. Many studies on treatment seeking behaviour have recognized age, education, residency, marital status, religion, and other socio-cultural variables as factors that explain human behaviour on treatment practices [10; 11]. None of these studies, however investigated in detail regional variation. It is interesting to note that descriptive analysis of the data we consider below showed considerable regional variation [4]. Surprisingly, the statistical significance of such regional variations has not been investigated, see 2006/07 Namibia DHS report, Chapter 11. This motivated the present study.

Explaining areal variations in treatment seeking behaviour has important implications for regional policy makers, especially for better informed decision making. By highlighting the spatial characteristics of each region, health promotion campaigns can be designed for targeted resource allocation and improved delivery of services [12]. Furthermore, spatial analysis can be used to incorporate any unmeasured and unobserved contextual factors such as cultural beliefs. From a statistical view point, spatial analysis adjusts for clustering at individual and community level inherent in nested sampling designs. Geographical information system (GIS) have been used in such initiatives, but they lack substantive statistical testing [13]. In this paper, a spatial multinomial probit model with ordered categories was employed to analyze timing of visits to health facility. It should be noted that logistic regression models and duration models have also been employed to study health seeking behaviour. Under the logistic regression the primary question is whether treatment was sought on time (1 = yes or 0 = otherwise). Duration models apply where the actual time of action is available. In this case study the response is segmented into: 0=same day, or 1=a day after or 2=two days or 3= three day and more after the onset of illness, which is evidently ordinal in nature. While estimating this model we adopted a Bayesian approach, because of the complexity of the model and as well as permit capturing of uncertainties associated with parameter estimation.

Now the rest of the paper is structured as follows. The data used in the analysis is described in Section 2.1. The methodology is described in Section 2.2 and results follow in Section 3, and we concluded in Section 4.

2 Methods

2.1 Data

Data used in this analysis was collected as part of the Namibia Demographic and Health Survey conducted in 2006/7. In part the survey provided information on childhood illnesses occurrence, prevention and treatment seeking behaviour. The survey employed a two-stage sampling design, with strata devised along the urban and rural as well as along the thirteen regions. At first stage, 500 clusters were randomly selected proportional to size, and at second stage a total of 9,200 households were systematically chosen from the selected clusters. A questionnaire was then used to collect data from women of ages 15-49 years. A total of 9,800 women were interviewed with a response rate of 92%. Briefly, information were collected on background characteristics, women status and decision making and recent episodes of childhood illnesses and responses to illness including fever/cough, diarrhoea and acute respiratory infection. Respondents were asked, "Had child had diarrhoea/fever/cough in past 2 weeks", "Have diarrhoea/fever/cough now" and "What did you do first when had diarrhoea/fever/cough" as well as subsequent actions when diarrhoea/fever/cough persisted. Further details on other data collected are given in the survey report [4].

For spatial analysis we used region and constituencies as spatial units. Regions and constituencies are second and third levels of administration in Namibia and due to decentralization, diseases control programmes are currently being implemented at regional/district level by the relevant health management team. As such spatial analysis at regional or constituency level is relevant for decision-making in diseases control and preventions.

2.2 Statistical model

In this section, we outline the model considered for analyzing delay in seeking heath care. The delay can be classified in days that elapsed before treatment was taken or before a visit to the health facility. Treatment can be sought the same day (0) or the day after (1) or after two days (2) or three or more days (3). This falls naturally into ordered categorical response, Y, of delay. Cumulative threshold models are often assumed for ordered categories. It is stipulated that Y is a categorized version of the latent variable U [14],

$$U = \eta + \varepsilon,$$

obtained through the threshold mechanism

$$Y = r \Leftrightarrow \theta_{r-1} < U < \theta_r, r = 1, \ldots, k,$$

with thresholds $-\infty = \theta_0 < \theta_1 < \ldots < \theta_k = \infty$. Assuming the error variable ε has the distribution function F, then Y obeys a cumulative model [14].

$$P(Y \leq r) = F(\theta_r - \eta) \tag{1}$$

where η is the predictor. The common choice for ε is the logistic or standard normal leading to either cumulative logit or probit model respectively. For identifiability one of the thresholds is set to zero and an intercept is included in the model as a fixed effect. Normally the last category is set to zero, i.e $\theta_k = 0$. The predictor η is specified for each care–giver i as

$$\eta_i = w'\gamma + f_{spat}(s_i). \tag{2}$$

where w' is a vector of fixed covariates and $f_{spat}(s_i)$ is the spatial effects of district, $s_i \in (1,\ldots,S)$, where care-giver i lives. In a further step we may split up the spatial effect f_{spat} into a spatially correlated (structured) and an uncorrelated (unstructured) effect $f_{spat}(s_i) = f_{str}(s_i) + f_{unstr}(s_i)$. A rationale is that a spatial effect is usually a surrogate of many unobserved influences, some of them may obey a strong spatial structure and others may be present only locally. By estimating a structured and an unstructured effect we aim at separating between the two kinds of factors. As a side effect we are able to assess to some extent the amount of spatial dependency in the data by observing which one of the two effects is larger. If the unstructured effect exceeds the structured effect, the spatial dependency is smaller and vice versa. Such models are common in spatial epidemiology, see e.g. Besag *et al* [15]. Here we assumed that ε follow a standard normal distribution, hence we have a cumulative probit model or a multinomial probit model with ordered categories, see Tutz [14] , i.e.

$$P(Y \le r|\Omega) = \Phi(\theta_r - \eta),$$

where Ω is a set of all parameters.

We implemented a Bayesian approach to fit the model (2). For Bayesian inference all parameters are assumed unknown and random and priors are assumed. The diffuse priors are suitable for fixed effects. For the threshold parameters θ_k, again, the diffuse prior, $p(\theta_k) \propto constant$, is a suitable choice. Markov random fields are assumed for spatial effects following Besag *et al* [15]; Fahrmeir and Lang [16]. This assumes that the mean for each area $f_{str}(s_i)$, conditional on the neighbouring areas, has a normal distribution with mean equal to the average of neighbouring areas $f_{str}s_l$, and variance inversely proportional to the number of neighbours m_i. Under contiguity, with $w_{il} = 1$ if areas i and l are adjacent and $w_{il} = 0$ otherwise, the CAR prior has the form,

$$f_{str}(s_i)|\{f_{str}(s_l);\sigma^2_{str};l \sim i\} \sim N\left(\frac{1}{m_i}\sum_{l\sim i} f_{str}(s_l), \frac{\sigma^2_{str}}{m_i}\right) \tag{3}$$

where $l \sim i$ denotes adjacency of areas l and i on the map, σ^2_{str} is a spatial variance, which controls the degree of smoothness. At a further step of hierarchy σ^2_{str} is modelled using the inverse Gamma (IG) with known hyperparameters $a = b = 0.001$. This gives a weakly informative but proper prior. For moderate to large data sets results are rather insensitive to the choice of a and b. However, because of the known concerns about this prior's possible informativity, a sensitivity analysis was carried out. The unstructured extra-multinomial heterogeneity was estimated using an exchangeable normal prior, $f_{unstr}(s_i) \sim N(0,\sigma^2_{unstr})$, where σ^2_{unstr} measures the degree of heterogeneity, which again was assigned an IG hyperprior.

In principal, having specified priors in the second stage, hyperparamaters are specified in the third level of the model hierarchy. Basically, this is a fully Bayesian inference approach. Inference then is based on the posterior distribution, which constitutes a product of priors and the likelihood function of the data. Normally this mixture of equation reads to analytically intractable high dimensional distribution. Sampling by Markov Chain Monte Carlo (MCMC) techniques are often used to obtain estimates for the model. Based on Fahrmeir and Lang [16], we use Metropolis-Hastings algorithm and Iterative Weighted Least Squares proposal for simulation sampling. A Gibbs sampler is also possible for the probit model if this is assumed.

2.3 Delay in seeking health care

We define the following four-ordered categorical response, Y_i, variable,

$$Y_i = \begin{cases} 0 & \text{same day} \\ 1 & \text{next day} \\ 2 & \text{two days} \\ 3 & \text{three or more days after.} \end{cases}$$

We model delays in seeking health with multicategorical probit models for the response (see equation 2), with $y_i = 3$ as the reference category. Our analysis depended on the following covariates:

AgeC age of the child (categorical)

AgeM age of the mother (categorical)

Dec decision making on spending money and say on health care (binary)

Res residence of care-giver (categorical)

Educ education of the care-giver (categorical)

SEduc education of the spouse (categorical)

SES wealth quintile (categorical)

All categories are coded in effect coding. Then we model the $P(Y_i \leq r|\eta_i), r = 0, 1, 2$ with predictor,

$$\eta_i = f_{spat}(s_i) + \gamma_1(AgeC) + \gamma_2(AgeM) + \ldots + \gamma_k(SES),$$

with spatial component and categorical fixed covariates as listed above. We used `BayesX` [17] to implement the model (2) using a fully Bayesian approach via MCMC. To avoid problems of mixing and convergence of the MCMC samples of threshold parameters, we implemented large sample iterations of 33,000 with 3,000 burnin and thinned every 30th observation for convergence assessment and parameter estimations. The fourth threshold category was assumed zero for identifiability of the model. Hyperpriors for the structured and unstructured spatial priors was assumed a=0.001 and $b = 0.001$ for both. Convergence was assessed through autocorrelation functions and trace plots.

3 Results

3.1 Descriptive Results

Tables 1 show the distribution in health seeking for diarrhoea and fever/cough with notable differences between days, but no difference by type of illness. About 10.7% and 12.7% report seeking health care for diarrhoea and fever on the same day respectively, while those seeking care a day after were 26.6% and 30.6% respectively. Delayed health care (after 48 hours) were about 60% for both illnesses.

Table 1: Percentage distribution by days delayed in seeking treatment for diarrhoea and fever.

Treatment seeking	Diarrhoea		Fever/Cough	
	Percentage	(n)	Percentage	(n)
Same day ($y = 0$)	10.7	(39)	12.7	(78)
A day after ($y = 1$)	26.6	(86)	30.6	(188)
Two days after ($y = 2$)	31.0	(113)	28.6	(176)
Three days or more after ($y = 3$)	34.6	(126)	28.1	(173)
Total	100.0	(364)	100.0	(615)

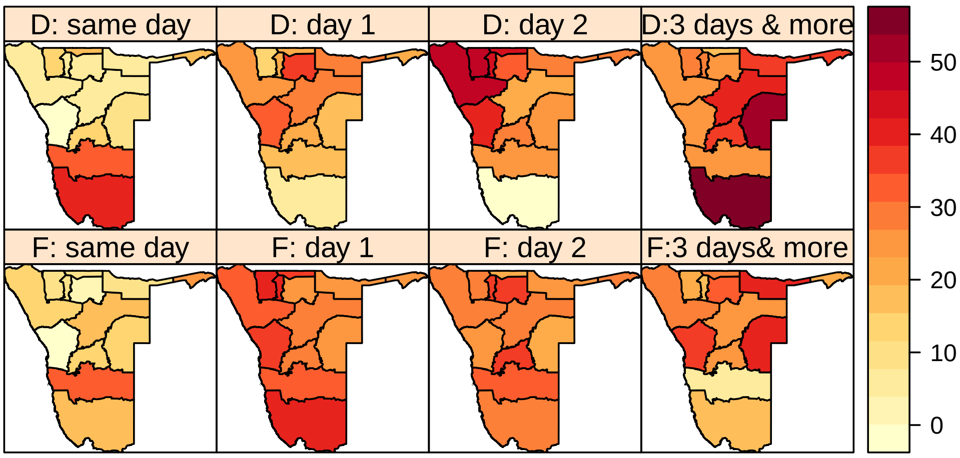

Figure 1: Geographical distribution in delays for fever (F) and diarrhoea (D). Shown are percentages seeking health the same day, or a day after or two days after and three or more days after.

Figure 1 shows regional variability in percentage seeking care each day for up to three days after onset of diarrhoea and fever. For diarrhoea, we observed a percentage of over 40 seeking care in Karas and Hardap regions seeking care on day 0, and corresponding low percentages observed in the northern regions. With regards seeking health care a day after diarrhoea, about 30% of respondents were observed in Erongo and Oshikoto. On day 2, a good proportion was observed in Kunene, Omusati, Oshana and Ohagwena regions. Timing of treatment for fever was rather delayed in all regions, except Hardap that reported about 20% seeking health care on the day of illness. Most regions showed a high response for fever treatment on day 1 after the onset of fever.

With regards to the mean duration in the timing of treatments, Table 2 shows variability across selected covariates. The duration of delay does not vary by age of the child, however considerable differences were noted with respect to the age of the mother, with older mothers likely to seek care the same day for diarrhoea (1.33 $\pm$0.58 days). Nevertheless, this is not quite clear for fever/cough. For those in urban areas, the majority visit health facilities much earlier after onset of diarrhoea and fever (2.27$\pm$2.04 and 1.88$\pm$2.35 days respectively). A similar picture was obtained with regards to maternal education and wealth quintile. Those who obtained higher education level were quicker at seeking health care for both illnesses (1.60$\pm$1.82 and 1.30$\pm$1.35 days for diarrhoea and fever respectively) relative to those without education (3.96$\pm$3.87 and 2.63$\pm$3.66 days for diarrhoea and fever respectively). Care-givers in the richest category sought health care much earlier (1.87$\pm$1.77 and 1.44$\pm$1.28 days for diarrhoea and fever respectively) compared to those in the poorest category (2.91$\pm$3.34 and 2.26$\pm$2.23 days for diarrhoea and fever respectively).

Furthermore, the result of the ordinal model for diarrhoea are shown in Table 3, where estimates of the threshold parameters θ_1, θ_2 and θ_3 for categories "same day", "one day after" and "two days after" are presented. For interpretation of the threshold parameters note that higher (lower) values of the predictor corresponds to early (delayed) timings in seeking or initializing treatment. For example, a negative sign of θ_1 signifies a shift to the left side of the latent scale, which translate to lower probability of seeing care in the category "same day". The converse is true. For those having diarrhoea, there was a significant decreased effect of the threshold for category "same day" (θ_1=-1.93, 95% CI: -2.17, -1.69), while for category "one day after" there is higher probability of seeking care compared to "same day" (θ_2=-0.27, 95% CI:-0.43, -0.11), and this propensity increased at "two day after" (θ_3=0.94, 95% CI:0.76, 1.14).

It is also observed that among the determinants of delay living in urban areas, without having formal education and being of medium socio-economic position were significantly associated with health seeking when a child has diarrhoea (Table 3). Urban residents were more likely to delay health seeking compared to their rural compatriots (γ=-0.29, 95% CI:-0.46, -0.11) while having no education increased the chance of early treatment compared to higher education (γ=1.68, 95% CI: 0.019, 3.35). Furthermore, although having secondary or primary education was not significant, the results showed an increased probability of delayed treatment with increased education level. For wealth quintile, the result show a U-shape with a significant association at medium level (γ=0.78, 95% CI: 0.18, 1.25).

Spatial variation in region-specific effects are plotted in Figure 2, where the maps presents the effect of early or delayed initialization of treatment for diarrhoea (Figure 2) and fever (Figure 3). In both cases, the maps on the left panel presents the region-specific posterior means while those on the right hand panel gives the region-specific posterior probabilities associated with the initiation of treatment of diarrhoea (map (a)) and fever (map (b)) respectively. For the posterior means map, the dark areas indicate those positively (early) related effects to the response, while white areas are those with negative effects (delayed timings). On the other hand for the probabilities maps,

Table 2: Mean delay from onset of diarrhoea and fever and the first visit to health facility in Namibia by selected covariates.

Variable	Diarrhoea		Fever/Cough	
	Mean	(SD†)	Mean	(SD†)
Age of child (month)				
<6	2.69	(2.53)	2.17	(2.08)
6-11	2.10	(1.64)	1.85	(1.46)
12-23	2.63	(2.59)	2.12	(1.78)
24-35	2.25	(1.57)	2.03	(1.56)
36-47	2.65	(2.85)	2.32	(3.93)
Age of Mother (years)				
15-19	2.30	(1.55)	2.07	(1.27)
20-24	2.48	(2.01)	2.05	(1.84)
25-29	2.26	(2.06)	1.75	(1.49)
30-34	2.87	(3.48)	2.23	(2.32)
35-39	3.14	(3.59)	2.55	(2.32)
40-44	2.71	(2.11)	2.45	(1.78)
45-49	1.33	(0.58)	3.14	(2.08)
Residence				
Urban	2.27	(2.04)	1.89	(2.35)
Rural	2.70	(2.67)	2.25	(2.05)
Maternal education				
None	3.96	(3.84)	2.63	(3.66)
Primary	2.24	(2.14)	2.31	(2.06)
Secondary	2.31	(1.96)	1.91	(1.71)
Higher	1.60	(1.82)	1.30	(1.59)
Wealth quintile				
Poorest	2.91	(3.34)	2.26	(2.23)
Poor	2.36	(2.02)	2.39	(3.09)
Medium	2.55	(2.14)	2.11	(1.71)
Rich	2.63	(2.42)	1.98	(1.91)
Richest	1.87	(1.77)	1.44	(1.28)
Own decision making				
Spending money	2.76	(1.92)	3.00	(5.38)
Say on health care	2.16	(1.64)	2.02	(1.58)

†SD=Standard deviation.

white areas imply significant positive relationship with the response, black areas denote significant negative region-specific effects while the grey areas represent no significant region-specific effects. The result from Figure 2 shows that Omusati was the only region with a significant positive (early) effects in initiating treatment for diarrhoea, while Hardap and Karas regions show a significant negative (delayed) effects. Other regions were not statistically significant despite showing positive or negative effects in the map (Figure 2a).

Table 3: Fixed effects of selected covariates on delay in diarrhoea patients

Variable	Mean	SE†	95% Credible	Interval
Threshold parameters				
θ_1	-1.93	(0.12)	-2.17	-1.69
θ_2	-0.27	(0.08)	-0.43	-0.11
θ_3	0.94	(0.09)	0.76	1.14
Age of child (month)				
<6	-0.12	(0.35)	-0.81	0.56
6-11	0.39	(0.33)	-0.26	1.04
12-23	0.16	(0.31)	-0.44	0.76
24-35	0.09	(0.35)	-0.60	0.77
36-47	0.22	(0.42)	-0.59	1.03
48-60	0			
Age of mother				
<20 yr	-0.11	(0.16)	-0.42	0.20
20–29	0.041	(0.08)	-0.16	0.23
30–39	0.011	(0.12)	-0.21	0.25
40-49	0			
Residence				
Urban	-0.29	(0.09)	-0.46	-0.12
Rural	0			
Education of mother				
None	1.68	(0.48)	0.012	3.35
Primary	0.83	(0.62)	-0.264	2.17
Secondary	-0.05	0.12	-0.26	0.19
Higher	0			
Wealth Quintile				
Poorest	0.57	(0.36)	-0.18	1.25
Poor	0.62	(0.34)	-0.07	1.26
Medium	0.78	(0.34)	0.18	1.25
Rich	0.59	(0.37)	-0.13	1.32
Richest	0			
Decision making				
Money use alone	0.77	(0.67)	-0.54	2.07
Money use with partner	-0.63	(0.61)	-1.82	0.56
Money use with others	0			
Health care alone	-0.06	(0.09)	-0.25	0.12
Health care decision with partner	0.04	(0.38)	-0.70	0.79
Health care decision with others	0			

†SE=Standard error.

Similarly, the result on timing of visits to health facilities and onset of fever are in Table 4. The threshold parameters for ”same day”, ”one day after”, and ”two day after” are θ_1 = -1.82 (95% CI: -2.29,1.35), θ_2 = -0.12 (95% CI: -0.56, 0.32), and θ_3 = 1.13 (95% CI: 0.68, 1.58) respectively. The result also indicates delay in seeking health by day 0 and an increased chance of hospital visit by

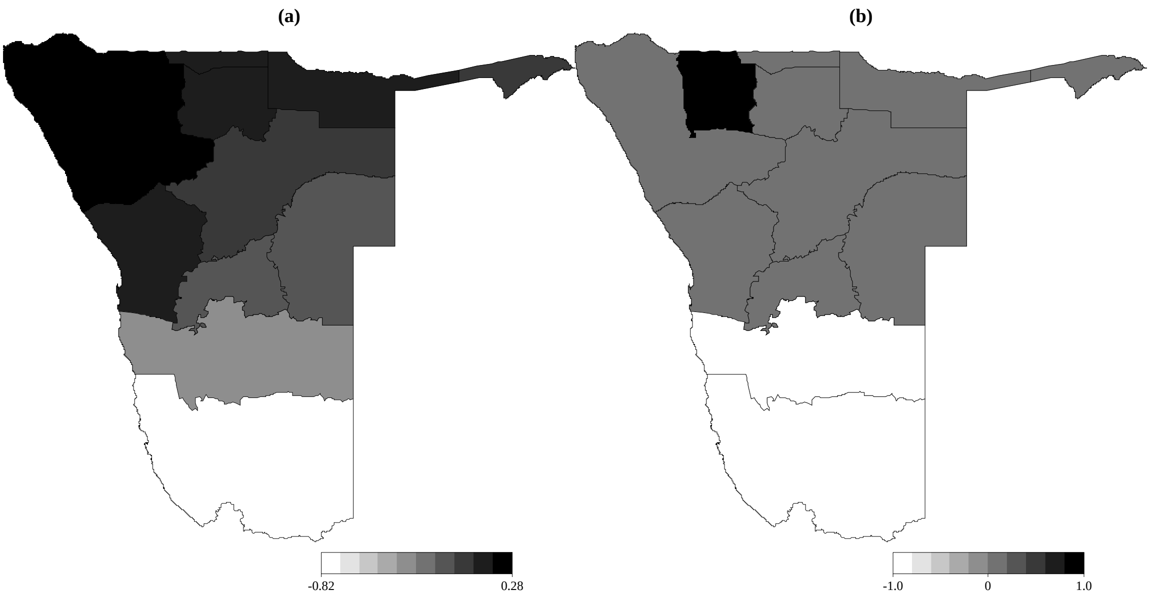

Figure 2: Posterior means (left panel) and probabilities (right panel) of the region-specific effects on timing or delays in initiating treatment for diarrhoea for a nominal level of 80%.

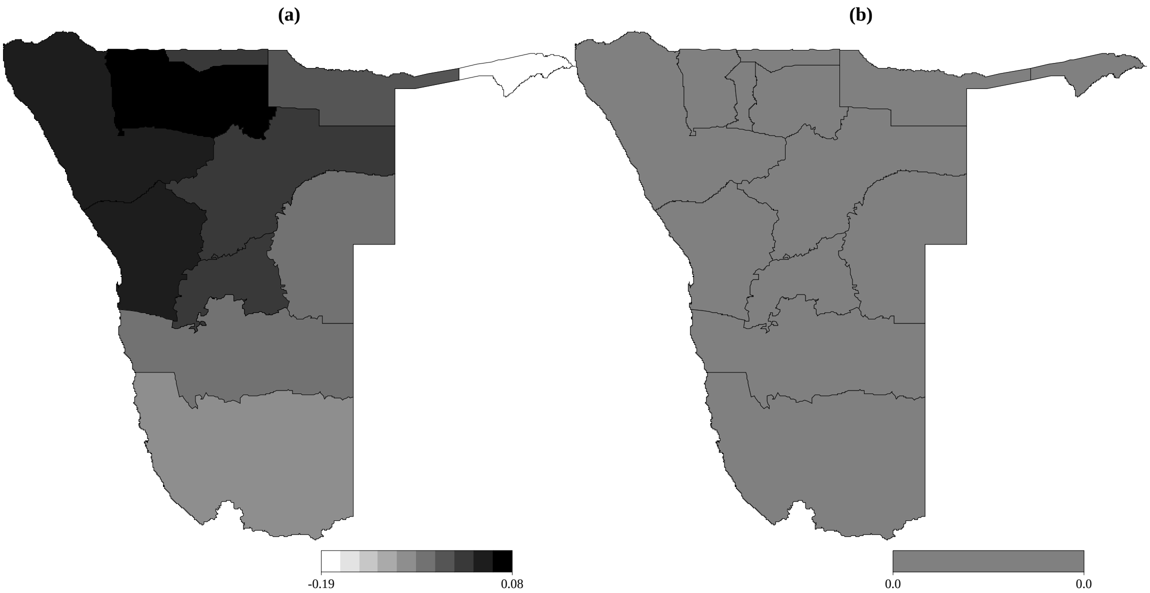

Figure 3: Posterior means (left panel) and probabilities (right panel) of the region-specific effects on timing or delays in initiating treatment for fever for a nominal level of 80%.

Table 4: Fixed effects of covariates on delay in fever patients

Variable	Mean	SE[†]	95% Credible	Interval
Threshold parameters				
θ_1	-1.82	(0.24)	-2.29	-1.35
θ_2	-0.12	(0.22)	-0.56	0.32
θ_3	1.13	(0.23)	0.68	1.58
Age of child (month)				
<6	-0.27	(0.19)	-0.52	-0.03
6-11	-0.05	(0.20)	-0.29	0.18
12-23	0.02	(0.19)	-0.21	0.26
24-35	0.19	(0.20)	-0.07	0.26
36-47	-0.21	(0.22)	-0.49	0.06
48-60	0			
Age of mother				
<20 yr	-0.17	(0.34)	-0.63	0.25
20–29	-0.49	(0.17)	-0.93	-0.15
30–39	-0.49	(0.28)	-0.85	-0.13
40-49	0			
Residence				
Urban	0.08	(0.17)	-0.12	0.28
Rural	0			
Education of mother				
None	-0.11	(0.21)	-0.39	0.14
Primary	-0.07	(0.17)	-0.12	0.27
Secondary and higher	0			
Wealth Quintile				
Poorest	-0.03	(0.28)	-0.37	0.34
Poor	-0.05	(0.27)	-0.39	0.25
Medium	-0.04	(0.22)	-0.27	0.32
Rich	-0.27	(0.23)	-0.56	0.01
Richest	0			
Decision making				
Money use alone	-0.17	(0.31)	-0.54	0.22
Money use with partner	-0.03	(0.23)	-0.34	0.24
Money use with others	0			
Health care alone	0.29	(0.11)	0.08	0.51
Health care decision with partner	0.13	(0.18)	-0.09	0.39
Health care decision with others	0			

[†]SE=Standard error.

day 2 after fever. It is further noted that infants were delayed compared to those aged 4 years or more (-0.27, 95%CI: -0.52, -0.03) while care-givers who were 20 years old and above were likely to delayed health seeking. Care factors such as making own decision with regards to deciding own health care also influenced early visit to a facility.

With respect to the region-specific effects as shown in Figure 3, it is observed that based on probability maps, none of the regions showed significant effects with timing of health care. However, they do provide important information on the geographic extent of treatment seeking behaviour as most regions (left panel) showed a positive (early) effects on timing of visiting a facility except for Caprivi region, which shows a negative (delayed) effect.

4 Discussion

The study analyzed patterns of timing of treatment for children who had diarrhoea and fever based on survey data collected in Namibia in 2006. The main objective was to investigate the spatial variation of such patterns having controlled for socio-economic variables of the caregiver.

In Namibia, as in most least developed countries, the level of health care utilization is low, and when a decision has been taken to seek care is often delayed. The study has shown significant spatial variation in region specific-effects in the timing of visit to the health facility. These effects are surrogates for some unmeasured or unobserved effects such as cultural beliefs that might be correlated to ethnicity or socio-economic status that were not captured in the data collection [18]. Studying spatial effects at region level masked some of the effects at sub-region level. This suggests the fact that different factors operate at different levels differently [19]. It is also suggestive of different forms of clustering at different levels of spatial resolution.

Having controlled for spatial dependence, the fixed effects showed that care factors are related to utilization of hospital. Care factors as measured by travel time difficulties, money needed and availability of transport does play some role in timing of visits to health facilities. Timing of visits to hospitals is also a question of who makes decisions over issues which measures women autonomy at home. Distance come into play here, and all these care factors considered here in one way or the other are related to distance. For example cost and availability of transport and travel time are directly related to distance. Being near the hospital would reduce the timing of visit. Distance has been studied by quite a number of authors [13; 20–26]. The weak link in this study is that we did not directly model effects of distance. We intend to explore this factor in our ongoing research.

While age of the mother, residence, education of mother or socio-economic position were not statistically related to timing of visit to health facility, other studies indicated that these are important predictors in explaining treatment seeking behaviour [27; 28].

Finally our findings have far reaching implications for malaria elimination. The low utilization of health care services is worrisome because achievement of elimination goals hinges mainly on increased and improved usage of health care systems. Of particular concern is that the delay is evident in areas where malaria is a problem, for example, in Caprivi region. It is unlikely that on the day fever is observed, care givers as it is in many malaria African regions, would rather give home treatments such as tepid sponging, herbs or modern medicines bought or kept at homes. Finding from national survey of 2006 point towards the fact that this is not the direction in Namibia, because the majority (73%) seek treatment from health facility [4]. With regards to diarrhoea, a similar picture is displayed. About 82% point to the fact that a health facility is the first place where treatment is sought. What is crucial is to establish factors contributing to the delay.

The spatial patterns may have important potential implications for research and health policy planning purposes [12]. First, the maps can generate leads for in-depth epidemiologic or geographic studies that may shed light on factors contributing to such human behaviour. Secondly, findings may help policy decision makers to pinpoint areas that need immediate health promotion campaigns to be designed that can ensure behaviour change. Thirdly, the maps may contribute to developing and prioritizing health targets at the district-area level. Fourthly, results of this study could form basis for distributing and targeting interventions across geographical zones.

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