Accounting for Spatial Interactions in the Demand for Community-Based Health Insurance: A Bayesian Spatial Tobit Analysis

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Abstract

Community-based health insurance (CBHI) has emerged as an effective alternative to provide households in rural areas of developing countries coverage against diseases. Previous studies have shown that the demand for coverage against diseases is increasingly high in rural areas. Most of these studies have used the contingent valuation method to assess the demand for CBHI. Nevertheless, these studies have failed to address potential spatial interactions in the demand for CBHI. This may likely bias the estimates and compromise policy-making. This paper investigates the spatial interactions in the demand for CBHI in a developing country setting using a spatial autoregressive Bayesian Tobit model. Results suggest that there are spatial interactions in the demand for CBHI and parameter estimates derived from the spatial Bayesian Tobit model are more precise compared those from either the standard Tobit or standard spatial autoregressive models. Our finding indicates that households in a village are more likely to pay for CHBI when on average their counterparts in the same village are willing to do so. This information is of interest to policy makers to design health insurance packages including the premium for rural households.

Keywords: Community-based health insurance, contingent valuation method, spatial interactions, spatial autoregressive Bayesian Tobit.

JEL Classification: C21, C34, I38.

1. Introduction

Recent years have seen growing use of the theory of risk and insurance in countries seeking to improve the accessibility of low-income households to adequate health care. The undergoing health reforms of these countries reflect the important role of health in achieving economic growth. Indeed, sickness generates significant economic, social costs and acts negatively on the potential of low-income households to produce and invest. Thus, reaching low-income households in developing countries with adequate health care and social protection has become a priority for many policymakers, international organizations and NGOs. As a result, Community-Based Health Insurance (CBHI) has emerged as an alternative risk protection measure for low income households (BIT 2002; Ekman 2004; ILO 2006; Jakab and Krishnan 2001, 2004; Preker et al. 2001; WHO 2001). The impact of CBHI on the low-income households is highlighted by the International Labour Office (ILO 2006, , p.1) in these terms: "*by helping low-income households manage risk, microinsurance can assist them to maintain a sense of financial confidence even in the face of significant vulnerability*". CBHI is defined by Churchill (2006, , p.12) as : «*... the protection of low-income people against specific perils in exchange for regular premium payments proportionate to the likelihood and cost of the risk involved*». The main characteristics of CBHI are the followings: voluntary membership, non-profit objective, link to a health care provider (often hospital in the area), and risk pooling relying on mutual aid/solidarity (Ahuja and Jütting 2004, , p.5). Estimating what the low-income households will pay for CBHI is important for policy making decisions since it helps define the best strategy to adopt.

There has also been a profusion of research papers on the estimation of household demand for CBHI (Ataguba, Ichoku, and Fonta 2008; Bärnighausen et al. 2007; ; Dong et al. 2004; Dror, Radermacher, and Koren 2007; Wang et al. 2005). However, most of, if not all, the empirical models underlying these studies, though rigorous, do not account for neighborhood effects of households' spatial interactions with other households residing in the same village or in geographically proximate villages. If plagued by spatial dependence existed in the demand for CBHI, these estimates derived from those studies may be biased and inefficient. Spatial dependence can be ascribed to the situation where observations on the dependent variable (or the error term) at one location is correlated with observations of the dependent variable (or the error term) at other locations. In rural areas of many developing countries, the likelihood of neighborhood effects is particularly high, due primarily to sharing of information about new technology, copy-catting, respect of norms and traditions. Thus, in estimating the demand for CBHI, it is important to account for spatial interactions among households. Failure to do so may result in misleading statistical inferences.

Spatial interactions have been studied in most cases where the dependent variable is continuous (Brueckner and Saavedra 2001; Case 1992; Conley 1999; Garrett and Marsh 2002; Jayet 1993; Kelejian and Prucha 2001; Le Gallo 2002; Lee 2004), but only very few studies address the spatial interactions with discrete choice dependent variable (Beron and Vijverberg 2003; Case 1991; LeSage 2000) and censored dependent variable. In fact, there are many situations in real life where households are confronted with two alternatives. For instance, in the case of CBHI, when confronted with the decision to pay a premium, households can decide whether to pay the premium or not. This household behavior can be modeled using discrete choice contingent valuation (CV) experiments. Since the seminal paper of Bishop and Heberlein (1979) followed by Hanemann (1984), the referendum or close-ended questions (CEQ) has been recommended since it is incentive compatible and mimics the regular consumption decisions where the consumer either buys or does not buy a good at a certain price. However, the CEQ could be subject to starting point bias, "yea saying" bias. Thus, open-ended questions (OEQ) could also be used since information obtained from each respondent is important because the maximum WTP is obtained directly. Results of experimental studies comparing the hypothetical WTP and the real WTP reveal that the hypothetical bias is not higher in OEQ than CEQ (List and Gallet 2001)[1]. Nevertheless, discrete choice CV and OEQ data may display spatial interactions when studying the households demand for CBHI. Furthermore, spatial interactions are seldom addressed in contingent valuation method (CVM) survey. To the best of our knowledge, no previous studies have examined the factors determining the demand for CBHI while allowing for the spatial interactions. This present study is an attempt to fill this void.

The rest of the paper is structured as follows. Section 2 presents the methodology used; Section 3 describes the data by providing a description of the survey. The empirical results of the study appear in section 4. Section 5 discusses the findings. Finally, section 6 concludes the paper with some policy implications.

2. Methods

This study uses two elicitation formats: CEQ and OEQ.

2.1 CEQ

2.1.1 CEQ without spatial interactions

In the discrete CVM especially in the single bounded-dichotomous choice (SBDC), there are two options available to respondents: the status quo $\left(q^{o}\right)$ and the proposed change $\left(q^{1}\right)$. As the proposed change (CBHI) corresponds to an improvement, $q^{1} \succ q^{0}$ and $v\left(p,q^{1},y,s,\varepsilon\right) > v\left(p,q^{0},y,s,\varepsilon\right)$ where $v(\bullet)$ is the indirect utility function which depends on p the price of the market goods, q the non-market item to be valued, y the level of income,

[1] There is no consensus with regard to optimal elicitation format among researchers, though OEQ dominates in the CVM applications. Some prefer CEQ primarily because of its incentive compatibility and the easy cognitive task required from the respondents. Still others favor OEQ because CEQ has proven to yield WTP measures significantly and substantially larger than those resulted from OEQ see e.g., .

s the individual's characteristics and ε a stochastic component allowing for random utility maximization.

In the survey, the respondent is informed that the change will cost a certain amount A and then asked whether he or she would be in favor of it at that price. The respondent will answer "yes" if only $v\left(p, q^1, y-A, s, \varepsilon\right) \geq v\left(p, q^0, y, s, \varepsilon\right)$ and "no" otherwise. Hence,

$$\Pr\{response\ is\ "yes"\} = \Pr\left\{v\left(p, q^1, y-A, s, \varepsilon\right) \geq v\left(p, q^0, y, s, \varepsilon\right)\right\} \tag{1}$$

By using the compensating variation measure, the quantity C satisfies:

$$v\left(p, q^1, y-C, s, \varepsilon\right) = v\left(p, q^0, y, s, \varepsilon\right)$$

Thus, $C = C\left(p, q^0, q^1, y, s, \varepsilon\right)$ represents the maximum WTP for the change from q^0 *to* q^1. It follows that the respondent will answer "yes" if the stated price is less than his WTP and "no" otherwise.

Hence, an equivalent condition to (1) is:

$$\Pr\{response\ is\ "yes"\} = \Pr\left\{C\left(p, q^0, q^1, y, s, \varepsilon\right) \geq A\right\} \tag{2}$$

Furthermore, it is assumed that $C\left(p, q^0, q^1, y, s, \varepsilon\right)$ is a random variable. While WTP for the change in q is known to the respondent, it is considered an unknown random variable to the researcher. Let $G_c(\bullet)$ be what the investigator assumes is the cumulative distribution function of *C*, and $g_c(\bullet)$ the corresponding density function. Then (2) becomes:

$$\Pr\{response\ is\ "yes"\} = 1 - G_c(A) \tag{3}$$

The form of the function $G_c(A)$ determines the econometric model to be estimated. If the $G_c(A)$ follows a standard normal distribution, then probit models can be estimated. In the case of a logistic distribution, Logit models should be estimated.

2.1.2 CEQ with spatial interactions

Prior to embarking in a spatial econometric analysis, it is important to ascertain of the presence of spatial dependence. The most commonly used test for the existence of spatial autocorrelation is the Moran's-I test (Moran 1950). The Moran's I statistic is:

$$I = \left(N / S_0 \right)\left(e^{'} W e / e^{'} e \right),$$

where e is a vector of ordinary least square (OLS) residuals and $S_0 = \sum_i \sum_j w_{ij}$, a standardization factor that corresponds to the sum of the weight for the non-zero elements in the spatial neighbor matrix *W.* The statistic *I* is asymptotically standard normal under the null hypothesis (absence of spatial interactions).We define the elements of spatial weights matrix *W* as follows: households are considered neighbors if they live in the same village. In other words, they are neighbors if they share the same border. This type of spatial contiguity matrix is known as social network spatial weights matrix (Anselin and Bera 1998) and is implemented in Stata using the user-written command « spwmatrix » (Jeanty 2010) and is implemented in Stata using the user-written command « spwmatrix ». Neighborhood effects are common in rural areas of developing countries, and this could be explained by the social interactions that could influence decisions of households for any type of health policy. This social network is most often powerful between the households of the same village since they share the same information.

Given the fact that the dependent variable is a binary variable, accounting for spatial interactions entails estimating a spatial Bayesian probit model due to multiple integrals that are intractable numerically. The spatial Bayesian probit model may be constructed as follows:

$$\begin{aligned} &Y^{*} = \rho W Y^{*} + X\beta + u \\ &\varepsilon \sim N\left(0, \sigma^{2} V\right) \qquad (4) \\ &V = diag\left(v_{1,} v_{2}, v_{3} \ldots . v_{N}\right) \end{aligned}$$

$Y = \begin{cases} 1 \ if \ \ Y^* > 0 \\ 0 \ if \ \ Y^* \leq 0 \end{cases}$ where Y^* is the unobserved latent dependent variable, Y is the observed value of the dependent variable, where *W* is an $N \times N$ spatial weights matrix, X is a matrix of explanatory variables, ρ is the spatial autoregressive parameter, ε *is* independent and identically distributed normal, with mean 0 and variance $\sigma^2 V$, where V reflects heteroscedasticity. It is worthy to note that if $\rho = 0$, the spatial probit model is equivalent to the standard binary probit model and there is not any spatial pattern in the demand for CBHI.

To estimate the spatial Bayesian probit model, we adopt the Gibbs Markov Chain Monte Carlo (MCMC). The Bayesian estimation of a spatial probit involves repeated sampling using the Gibbs Markov Chain Monte Carlo (MCMC) method (LeSage 1998). The MCMC procedure involves 1000 draws with 10% of them used as burn-in. By requiring the researcher to specify the distribution of each parameter conditional on the other parameters, the Gibbs sampling algorithm begins by taking draws from the conditional distribution associated with the first parameter or set of parameters (Timothy 2007). The advantage of the Gibbs sampler is that it simulates the continuous latent variable and then treats the data like a linear regression, in the sense that it treats the simulated variable as if it where the actual variable (Albert and Chib 1993).

2.2 OEQ

2.2.1 OEQ without spatial interactions

There are various methods to estimate the WTP in OEQ. In the current study, two econometrics models are used when analyzing WTP in CBHI. The first one is the ordinary least square (OLS) which is the traditional method used for analyzing OEQ in CVM (Bateman et al. 1995). Nevertheless, this ignores the censoring implying by zero bids and could result in biased and inconsistent estimates (Halstead, Lindsay, and Brown 1991). The second one is a tobit model based on the assumption that WTP values are censored at zero (see e.g., Bateman et al. 2006; Halstead, Lindsay, and Brown 1991).

For the OLS, the model is:

$$Y = X\beta + \varepsilon \tag{5}$$

All the variables in equation (5) are defined as equation (4) but here Y is a continuous variable.

The structural equation of the tobit model is as follows:

$$Y_i^* = X_i\beta + \varepsilon_i \tag{6}$$

Where, Y_i^* is a latent variable that is observed for values greater than zero and censored otherwise. The observed Y is defined by the following equation:

$$Y_i = \begin{cases} Y^* \ if \ Y^* > 0 \\ 0 \ \ if \ \ Y^* = 0 \end{cases}$$

The estimation of the tobit model is done by the maximum likelihood (ML).

Let us assume that the indicator function $I(Y_i)$ is:

$$I(Y_i) = \begin{cases} 0 \ if \ Y_i = 0 \\ 1 \ if \ \ Y_i \neq 0 \end{cases}$$

Then, the likelihood function of tobit model is:

$$L = \prod_i^N \left[\frac{1}{\sigma}\phi\left(\frac{Y_i - X_i\beta}{\sigma}\right)\right]^{I(Y_i)} \left[1 - \Phi\left(\frac{X_i\beta}{\sigma}\right)\right]^{1-I(Y_i)}$$

$\phi(\bullet)$ and $\Phi(\bullet)$ are respectively the standard normal density function and standard normal distribution function.

The log-likelihood function is:

$$LnL = \sum_{i=1}^N \left(I(Y_i)\right)\left(-\ln\sigma + \ln\phi\left(\frac{Y_i - X_i\beta}{\sigma}\right)\right) + \left(1 - I(Y_i)\right)\ln\left(1 - \Phi\left(\frac{X_i\beta}{\sigma}\right)\right)$$

The log-likelihood function of the tobit model has two parts: the first part is similar to the classical regression for the uncensored observations, while the second part corresponds to the relevant probability that an observation is censored.

2.2.2 OEQ with spatial interactions

2.2.2.1 Spatial interactions in OLS

In the presence of spatial effects, we assume that there is a residual effect that persists in the error term and causing the violation of the assumption of independence between the explanatory variables and the error term. This spatial dependence is taken into account by the spatial interaction matrix *W*. Moran's I statistic is first used to test for the spatial interactions. The rejection of Moran's I test of the null hypothesis (no spatial interaction) does not specify the type of model to be used. Indeed, if this test rejects the null hypothesis, then two types of models could be used: spatial autoregressive model (SAR) or spatial lag model, and spatial error model (SEM).

- **Spatial autoregressive model**

In the SAR models, it is assumed that the spatial interaction is found in the dependent variable. In other words, the dependent variable Y depends on the levels of Y in the neighboring units. The model is:

$$Y = \rho WY + X\beta + \varepsilon \tag{7}$$

With ε assumed to be classical, Y is the maximum WTP, ρWY is the spatially lagged dependent variable and W is the social network spatial weights matrix. The presence of Y on both the left and right sides of equation (7) means that there is correlation between the errors and covariates. Thus, the estimates will be biased and inconsistent if the OLS is used for estimation purpose. The null hypothesis of no spatial interaction is $H_0 : \rho = 0$.

The estimation of SAR is done by the ML, and the log-likelihood function of the SAR model is:

$$Ln\ L(\beta,\rho,\sigma) = -\frac{N}{2}\ln\pi - \frac{N}{2}\ln\sigma^2 + \ln\|A\| - \frac{1}{2\sigma^2}(AY - X\beta)'(AY - X\beta)$$

Where $\|A\|$ is the determinant of A and $A = I - \rho W$

From the first order condition, we have:

$$\hat{\beta}_{ML} = (X'X)^{-1}X'AY$$

$$\hat{\sigma}^2_{ML} = \frac{(AY - X\hat{\beta}_{ML})'(AY - X\hat{\beta}_{ML})}{N}$$

- **Spatial error model**

In the SEM, spatial interactions are found in the random part of the model. In this model, the error terms across different spatial units are correlated. Thus, violating the assumptions of uncorrelated error terms in OLS. As a result, the estimates are inefficient. The SEM is:

$$\begin{aligned} Y &= X\beta + u \\ u &= (Wu)\lambda + \varepsilon \end{aligned} \tag{8}$$

With ε assumed to be classical, Y is the maximum WTP, λ is the parameter representing the intensity of the spatial interaction between the residuals of the regression and the error term ε. The null hypothesis of no spatial interaction is $H_0 : \lambda = 0$. Most often the validation of the SEM model (rejection of H_o) is an indicative of omitted covariates that is left unattended. Thus, these omitted covariates are found in the random component.

The estimation of SEM is done by the ML, and the log-likelihood function of the SEM is:

$$Ln\ L(\beta,\rho,\sigma) = -\frac{N}{2}\ln\pi - \frac{N}{2}\ln\sigma^2 + \ln\|B\| - \frac{1}{2\sigma^2}(Y - X\beta)'\Omega(\lambda)^{-1}(Y - X\beta)$$

Where $\|B\|$ is the determinant of B *and* $B = I - \lambda W$

From the first order condition, we have:

$$\hat{\beta}_{ML} = \left[X^{'}\Omega(\lambda)^{-1}X\right]^{-1}X^{'}\Omega(\lambda)^{-1}Y$$

$$\hat{\sigma}^2_{ML} = \frac{\left[Y - X\hat{\beta}_{ML}\right]^{'}\Omega(\lambda)^{-1}\left[Y - X\hat{\beta}_{ML}\right]}{N}$$

The SAR and SEM could be combined to have a spatial autoregressive moving average[2] (Huang 1984) The SARMA is:

$$y = \rho Wy + X\beta + u \tag{9}$$

$$u = (Wu)\lambda + \varepsilon$$

Using robustness tests, we may test the spatial interactions of some forms in the presence of another form. Thus, the Lagrange multiplier (LM) test is used to test $H_0 : \lambda = 0$ from equation (9) or $H_0 : \rho = 0$ from equation (9). The failure to reject H_o by one of the two tests is used to select the appropriate model. Nevertheless, if the two tests reject the H_o, the robust form of the LM (RLM) based on Bera and Yoon (1993), Anselin et al. (1996) is used to select the appropriate model. For instance if the LM_{lag} and LM_{error} are significant but only the RLM_{lag} is significant, then the spatial lag model is the appropriate model to be used to account for spatial interactions.

2.2.2.2 Spatial interactions in tobit model

In the OEQ, we observe zero counts in the WTP for CBHI. Thus, to account for spatial interactions, a Bayesian spatial autoregressive tobit model (SARBT) is used. The model is

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[2] SARMA.

similar to the simple tobit model but here the spatial interactions are integrated in the model. Thus, the model is:

$$Y_i^* = \rho W Y_i^* + X_i \beta + \varepsilon_i$$

The variables in the models are described as in equations (6).

The estimation of parameters from the SARBT is computer complex, and cannot be done via analytic methods such as maximum likelihood. Therefore, the Bayesian approach developed by Lesage (LeSage 2000), Lesage and Pace (2009) were used via the Matlab software package. The model is estimated via the Monte Carlo Markov Chain estimation procedure. The Gibbs sampling is used to produce draws from a multitivariate truncated normal distribution in order to generate the unobserved utilities associated with the censored zero observations. Thus, by creating an artificial sampling from the sequence of complete conditional distributions for all parameters in the model, a set of estimates is produced and converges to the true posterior distributions of the parameters.

3. Data

A strategic plan for the promotion and development of CBHI in Cameroon by policymakers is adopted. It aims at: (a) putting in place CBHI per health district by 2015, (b) covering at least 40% of the population by the CBHI by 2015. A CV survey was then designed to estimate the WTP for CBHI of 369 rural households in Bandjoun (West province of Cameroon, Central Africa). The heads of households were interviewed using a face-to-face survey by a two-stage cluster sampling technique. First, six villages were selected based on population size and availability of public health care facilities. The six villages were: Tsela, Mbiem, Mbouo, Pète, Dja and Toba. Second, household heads in these villages were randomly selected. The elicitation format used was the CEQ or the dichotomous choice[3] where the respondent is

[3] It is also known as the take-it-or-leave it.

asked: “Would you be willing to pay for X CFA francs?” (X is randomly varied across respondents). This elicitation format was chosen since it is incentive compatible (Arrow et al. 1993) and places a low cognitive burden on the respondent. Furthermore an OEQ in the form of “What is your maximum amount that you will be wiling to pay for CBHI?” is asked to have more information on households’ WTP. The CV questionnaire was conceived and administered by following guidelines prescribed by Arrow et al. (1993); Carson (2000); Whitehead (2006) and Whittington (2002). In the scenario of the CV survey, CBHI was presented to the respondent; a budget reminder and the consequentialism[4] script were also integrated in the scenario. In other words, the scenario of the CBHI was described in detail to the respondent. This included the nature of the scheme, the organization, the membership criteria, and the expected benefits. Focus groups and pretest were performed before the final questionnaire. Each respondent of the final survey was assigned one of the following payments: 250, 350, 450, 550, 650 and 800 CFA francs.

4. Results

Table 1 provides the explanatory variables used and their descriptive statistics.

[Insert Table 1 about here]

The study was enriched by testing for spatial interactions. As revealed in Table 2, based on the OLS, the Moran’s I test is positive (3.91) and statistically significant at 1% level, implying that there are spatial interactions on the demand for CBHI. Thus, the spatial interactions are

[4] This script explicitly informs the respondents they should consider that the results of the study will have an actual effect and that the respondents must integrate this before answering the valuation question.

integrated in the analysis. Furthermore, the test on the null hypothesis on whether there are not spatial interactions in the SAR or SEM ($LM_{LagError}$=8.41) is rousingly rejected at 1% level. However, there are no spatial interactions in the probit model. As a result, we do not pursue the spatial probit model any further. Furthermore, the p-value of Moran statistic for the tobit (4.22) is highly significant at 1% level, suggesting that there are spatial interactions in the tobit model.

[Insert Table 2 about here]

In Table 3, we compare both the model without spatial interactions (a-spatial model) with the model that accounts for spatial interaction**.**

First and foremost, in the a-spatial model, there are three variables that affect the WTP for CBHI namely the health state, profession, and education. Indeed, the households with poor health status are more willing to pay than others and the higher is the education of the households, the higher is the WTP for CBHI. The positive sign and significant effect of the health status of the households on the WTP for CBHI seems to suggest that there is adverse selection. To mitigate adverse selection, the decision maker could establish a waiting period. Thus, after having joined the CBHI, affiliated rural households could wait two or three months before benefiting health insurance coverage in the health center. Obviously, this can discourage some members. Furthermore, the profession of the household is significant with a negative sign implying that respondents are farmers/sellers are less willing to pay than those who are self-employed or working in the private/public sector.

Secondly, by accounting for spatial interactions, the last two columns in Table 3 show that there is an efficiency gain when using spatial models. In fact, in the spatial models, in addition to the significance of the health state, profession and education, the distance and intensity of spatial interactions are statistically significant and most of the covariates in the spatial models have smaller standards errors as compared to the a-spatial models. The sign of the distance may be counterintuitive. But, the distance to the nearest public health facility has mixed results on households' WTP. In the empirical literature, the distance to the nearest health facility is found to have a positive effect on WTP in some studies (Asenso-Okyere et al. 1997; Asgary et al. 2004) while in other it has a negative effect (Dong et al. 2003; Jiang, Asfaw, and von Braun 2004). The positive sign may be explained as follows: when rural households have to incur transport costs to get to the hospital/clinic, they are relieved if the other costs are taken care off by the insurance, while those who live close by do not have these additional costs, which makes it easier to access health care. Furthermore, in the spatial models, the parameter ρ (the intensity of spatial interactions) are positive and highly significant at 1% level, confirming the spatial diagnostics test carried in Table 2.

[Insert Table 3 about here]

5. Discussions

The test of spatial interactions in the spatial models (SAR, SARBT) suggests the presence of spatial interactions in the demand for CBHI. These spatial interactions thus affect the WTP for CBHI. In fact, a change on an explanatory variable in a particular village will affect the WTP in this village (direct impact), but also the other neighboring household in the same village because of the spatial externality (the indirect impact). As shown in Table 3, the spatial autoregressive parameter is positive and highly significant $(\rho > 0)$, implying that households' buying behaviors are strategic complements. In other words, when the low-income households are willing to pay (or not pay) for CBHI in one particular village, other households residing in the same village are willing to do the same. This externality (imitation effects) in the demand for CBHI may be explained by the social norms that rule many rural areas in developing countries. This highlights mimicry or social conformity found in rural areas of many developing countries. This mimicry behavior seems to be intense in such communities and households behave the same manner in order not to stand out from the social norms. This social norm emerges through cultural values and is usually coordinated through the village head, the district head or the head of the family.

Therefore, policymakers must be conscious that space matters significantly in the demand for CBHI and must take this into account when designing health insurance packages for rural households and their premium as well. For instance, if policymakers or micro-insurance practitioners levy a high premium in one village for an attractive health insurance package and rural households are not willing to pay for CBHI, then their neighboring households might do the same due to spatial interactions. The converse might be true. If premiums are affordable and rural households are willing to pay for CBHI, then so might be their neighbors. Furthermore, there is an efficiency gain when using spatial models to account for spatial interactions. Lastly, the results seem to be sensitive to the elicitation format used to assess the demand for CBHI.

6. Conclusions

CBHI is considered as a health insurance tailored and designed for the low-income households who would otherwise not have formal insurance. The demand aspect of the CBHI seems to be important for policymaking. In other words, what the low-income households are willing to pay is important to policymakers for resource allocations. Most researchers usually employ CVM to simulate an artificial market where the analyst could assess the demand of low-income households for CBHI. Nevertheless, the assessment of this demand could be biased if there are spatial interactions in the demand for CBHI, affecting thus policy-making decisions. Therefore, the interactions of the agents with other heterogeneous agents are taken into account in the economic analysis. To the best of our knowledge, so far, no studies have attempted to account for spatial interactions in CBHI. Spatial interactions could be explained by social interactions among households within neighborhoods and may be crucial in the decisions of households. Furthermore, spatial interactions are seldom addressed in CVM. The overarching objective of the paper was to examine the determinants of demand for CBHI while allowing for spatial interactions by using a spatial econometric approach. Diagnostic tests for spatial dependence reveal the presence of spatial interactions in the demand for CBHI. Due to the presence of spatial interactions affect WTP for CBHI and the preponderance of a significant number of zeros in the dependent variable, we carry out the analysis using a spatial Bayesian tobit model. The Bayesian approach is also robust to heteroskedasticity. The estimated spatial autoregressive parameter is positive and significant, indicating that on average a household's WTP for CBHI in a particular village is not only explained by the explanatory variables associated with that household, but also by WTP of all other househlods residing in the same village. This finding suggests that households' buying behaviors are strategic complements. In other words, when a low-income household in a village turns down a high premium or approves of a low premium, then so might other households in the same village. This externality (imitation effects) in the demand for CBHI may be explained by the social norms that rule many rural areas in developing countries. Therefore, policymakers must be conscious of the importance of space when designing health insurance packages including the premium for rural households.

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Table 1: Description of the variables and summary statistics

Variable	Description	Mean	Standard deviation	Min	Max
Income	Income of the respondent (expressed in thousands of CFA francs)	37.13	44.85	7.5	202.5
Age	Age (number of years) expressed in thousand	42.25	12.44	22	82
Male	Gender of the respondent (1 if the respondent is a male, 0 otherwise)	0.61	0.49	0	1
Healhstate	Health status of the respondent (1 if the respondent has a poor or very poor health state, 0 otherwise)	0.26	0.44	0	1
Education	Level of education of the respondent (1 if the respondent has been to secondary school, 0 otherwise)	0.24	0.43	0	1
Farmer	Profession (1 if the respondent is a farmer/seller, 0 otherwise)	0.53	0.49	0	1
Meanstreatment	The means of seeking treatment when any member of the household falls sick (1 if conventional, 0 otherwise)	0.84	0.38	0	1
Involvement	Participation of the respondent in an association (1 if yes, 0 otherwise)	0.52	0.50	0	1
Distance	Distance between the house of the household and health public facility in kilometers	1.60	1.26	0.01	8

Table 2: Diagnostic test for spatial interactions

Statistic	Value	P-Value
OLS		
Moran's_I	3.91	0.00^{***}
LM_{error}	8.40	0.00^{***}
RLM_{error}	0.19	0.66
LM_{lag}	8.22	0.00^{***}
RLM_{lag}	0.01	0. 91
$LM_{LagError}$	8.41	0.00^{***}
Probit		
Moran's_I	-0.94	0. 35
LM_{error}	0.75	0.39
Tobit		
Moran's_I	4. 22	0.00^{***}

Notes : * $p < 0,10$, ** $p < 0,05$, *** $p < 0,01$.

Table 3: Spatial autoregressisve and Bayesian spatial Tobit

A-spatial model			**Model with spatial interactions**		
Variable	OLS	Tobit	Variable	SAR	SARBT
Age	0.002	0.002	Age	0.002	0.002
	(0.004)	(0.004)		(0.0002)	(0.002)
Male	-0.10	-0.13	Male	-0.08	-0.11
	(0.004)	(0.11)		(0.004)	(0.01)
Income	-0.0006	-0.0008	Income	-0.0008	-0.001
	(0.001)	(0.001)		(0.00005)	(0.00005)
Distance	0.05	0.06	Distance	0.06	0.06
	(0.04)	(0.04)		$(0.002)^{*}$	$(0.002)^{*}$
Meanstreatment	-0.13	-0.12	Meanstreatment	-0.11	-0.11
	(0.13)	(0.14)		(0.01)	(0.01)
Involvement	0.11	0.13	Involvement	0.11	0.13
	(0.09)	(0.10)		(0.005)	(0.01)
Farmer	-0.18	-0.21	Farmer	-0.17	-0.21
	$(0.09)^{*}$	$(0.10)^{**}$		$(0.005)^{***}$	$(0.01)^{***}$
Education	0.28	0.27	Education	0.29	0.26
	$(0.11)^{***}$	$(0.12)^{***}$		$(0.01)^{***}$	$(0.01)^{***}$
Healthstate	0.19	0.20	Healthstate	0.16	0.19
	$(0.11)^{*}$	$(0.12)^{*}$		$(0.01)^{*}$	$(0.01)^{**}$
Intercept	0.86	0.84	Intercept	0.50	0.51
	$(0.24)^{***}$	$(0.24)^{***}$		$(0.02)^{***}$	$(0.02)^{**}$
			ρ	0.36	0.36
				$(0.01)^{***}$	$(0.01)^{***}$

Notes: Standard errors are in parentheses. * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.SAR and SARBT are respectively the spatial autoregressive for the OLS and spatial autoregressive Bayesian Tobit.