MODELING THE RELATIONSHIP BETWEEN PERCEIVED NEIGHBORHOOD CHARACTERISTICS AND ADULT HOSPITALIZATION FREQUENCIES FRO A CROSS-SECTIONAL STUDY

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1. INTRODUCTION

Interest in the effects of neighbourhood or local area characteristics on health status and outcomes has increased in recent years; the feeling is that the context in which people live, as well as personal characteristics, affects their well-being and quality of life. Identifying which neighbourhood qualities and characteristics are more important to health is then a crucial issue not only for a better understanding of the connection between health and place, but also to assess health status of communities and to inform future health intervention strategies (Berkman and Kawachi, 2000).

Statistical modelling plays a central role in dealing with this issue. Generally speaking, one needs data on health status and other relevant characteristics of individuals and neighbourhoods. A statistical model is then used to shed light on the interrelationships among the quantities involved. Several studies of local urban area effects have been conducted focusing on the impact of neighbourhood characteristics on health outcomes after adjusting for individual status. They differ according to the population considered, the (response and explanatory) variables and the statistical models involved. The statistical approach used depends on the characteristics of the data and the specific questions to be answered; examples include: various (G)LM (Bowling *et al.*, 2006; Wen *et al.*, 2006; Wilson *et al.,* 2004; Abada *et al.*, 2007; Propper *et al.,* 2007) multilevel regression (Pickett and Pearl, 2001; Wen *et al.*, 2007; O'Campo, 2003), graphical models (Rajulton and Niu, 2005), spatial models (Chaix *et al.*, 2005 and 2006) structural equation (Weden *et al.*, 2008; Li and Chuang, 2009). A more comprehensive discussion of the conceptual framework behind these models can be found in Bellini *et al.* (2008).

In this paper the neighbourhood qualities we take into consideration are the perceptions that each individual has of a number of neighbourhood characteris-

This work is financially supported by University of Padua (grant number 062874).

tics. These are included in the model as individual rather than contextual variables (quantities computed for each neighbourhood and then associated to each individual living in that neighbourhood). Using individual perceptions about the neighbourhood may be seen as a limitation of the present study, when they should, in fact, be regarded as measures with error of the neighbourhood quality. Using the perceptions, however, may also be a strength for two main reasons. First, since conclusions on neighbourhood effect are sensitive to the neighbourhood definition that is adopted (Flowerdew *et al.* (2008)) – to the extent that spurious results may be found (Spielman and Yoo (2009)) – the fact that we avoid choosing a – necessarily arbitrary – specific definition leads to more robust results. In particular, geographic or administrative boundaries – which are the most common choices – may not be the appropriate definition when dealing with characteristics related to social interactions (Diez Roux, 2001); in this case the 'perceived' neighbourhood (which is the definition implicitly used here) may be a more appropriate choice. Second, it may be argued that the effect of the neighbourhood is not merely the result of its objective qualities, but also depends on subjective factors (this may be true in particular for social characteristics, but, even if we consider an eminently objective feature such as pollution, its effect on an individual depends on his personal degree of exposure). The connection between neighbourhood perceptions and health has already been discussed in the literature, and a variety of perceived aspects of the neighbourhood is considered by the various authors. Broadly speaking one may distinguish perception of the physical (or environmental) characteristics of the neighbourhood and perceptions related to the social capital; the latter may concern problems due to (anti-)social behaviour on the negative side and to social cohesion on the positive side. Some authors aggregate individual perception at the neighbourhood level and use the result as a contextual variable finding a significant effect (Pampalon *et al.*, 2007; Wen *et al.*, 2006). Pampalon and co-authors explicitely discuss the issue of whether aggregated individual perceptions are a suitable contextual variable. Perceptions of physical and social characteristics have also been used as individual (non contextual) variables. They were found to have a significant effect on health in Glasgow (UK) (Ellaway *et al.*, 2001); in Hamilton (Canada) (Wilson *et al.*, 2004) and among British over age 65 (Bowling *et al.*, 2006). In particular, the significance of the perception of physical problems in the neighbourhood is emphasized by the cited authors. Perceptions were significantly associated to asssessment of depression in Schaefer-McDaniel (2009). In previous studies a significant effect of social cohesion on adolescent health has been estimated (Abada *et al.*, 2007). Other authors estimated a more complex relationship involving an interaction between individual trust and a contextual variable measuring community trust (Subramanian *et al.*, 2002). Finally, using L.A.FANS data, it was found that social capital (as measured by the variables called closeknit, safe and neigh.satisf in Table 2) has a significant effect on self-reported health in poor and very poor neighbourhoods (Shin *et al.*, 2006).

On the response variable side we choose to consider the number of hospitalizations as the health outcome. The effect of neighbourhood quality on hospitalization frequency has been explored relatively rarely; evidence has been found of a negative relationship between socio-economic status of the neighbourhood and hospitalization frequency (Booth and Hux, 2003; Taylor *et al.*, 2006). This is unsurprising since hospitalization frequency in the general population is difficult to model due to the high proportion of zeroes generally observed. In this work we try to show that this inconvenience can be successfully dealt with through suitable models. Moreover, we prefer number of hospitalizations rather than the main alternatives, number of visits to a physician and perceived (self-assessed) health status, because the former is a more objective measure of health status with respect to perceived health and also, to a lesser extent, with respect to the number of visits to a physician. In prospect, it may also be interesting to model both hospitalizations and visits in a bivariate setting. A further alternative measure of health status would be having been diagnosed as suffering from specific pathologies; such a choice, however, would be appropriate for a study devoted to specific pathologies rather than a study concerned with general health.

The fact of using perception of the neighbourhood quality as explanatory variables is one more reason to prefer an objective measure of health conditions as the response variable: any association of self-reported health status to perceived neighbourhood quality may be spurious, since it may be driven by the overall attitude of the respondent (Pampalon *et al.*, 2007; Weden *et al.*, 2008). Moreover, it is worth saying that our purpose is not to infer a causal relationship between neighbourhood characteristics and health – the cross-sectional nature of the data that we use would not consent that, anyway – but merely to develop a statistical model for the association between the two quantities.

Bearing in mind all the above, we need, from a modelling point of view, an asymmetric model for count data (i.e., for integer response). A generalized linear model with Poisson response would be the most common choice in such a context. However, the relatively unusual choice of hospitalization data leads to a complication: in fact, the Poisson model proves to be inadequate mainly because of a high proportion of zeroes, which cannot fit into a Poisson assumption. This is a relatively common issue in applied statistics literature, particularly in epidemiology, and the typical solution is to replace the Poisson assumption with the Zero-inflated Poisson or the Negative-Binomial distribution (Böhning *et al.*, 1999; Hur *et al.*, 2002; Lee *et al.*, 2006), in the context of urban studies, on the contrary, this option is seldom, if ever, taken. Because we consider hospitalization data, however, we could not ignore the issue, and we want to stress that this has proved relevant in interpreting the results.

2. DATA

We consider the data collected within the Los Angeles Family and Neighbourhood Survey (L.A.FANS) (Peterson *et al.*, 2004), which has already been exploited in the literature. The Los Angeles Family and Neighbourhood Survey (L.A.FANS) is a panel study performed by the RAND corporation. In L.A.FANS a representative sample of households in Los Angeles County has been interviewed in two waves (2000-2001 and 2004-2005). The study is aimed at offering a better understanding of neighbourhood effects. For this reasons questionnaires ask for informations concerning neighbourhood characteristics and the random sample is stratified by neighbourhood – 65 neighbourhood (census tracts) in L.A. county were considered. Also, poor neighbourhoods and families with children are oversampled.

In the first wave, which is considered here, 3085 households were sampled (of which, 777 cases were households without children and 2308 with children) and for each of them interviews were made to a Randomly Selected Adult (RSA) and, if the household had children, a Randomly Selected Children (RSC), a Sibling (SIB) and the Primary Care Giver (PCG); in the end 2620 adults, 3161 children (2001 RSC and 1160 SIB) and 2044 caregivers completed the interview (see Figure 2.3 and Table 2.8 in Peterson *et al.*, 2004). In this work we do not consider family issues, so we consider only answers from the 2537 RSA interviewed who responded to the question concerning hospitalizations.

In Table 1 we briefly describe the personal characteristics taken under consideration. In Table 2 we list variables describing the characteristics of the neighbourhood as perceived by the respondent (which are the only information on neighbourhood considered here). Such variables are related to social resources availability (social cohesion and trust, informal social control), environmental stressors (safety) and general satisfaction with neighbourhood. The responses on these topics are highly dependent, so it is advisable to build indicators which sum up subsets of them rather than to use all of them as covariates. A similar approach can be found in the literature too (Ellaway *et al.*, 2001; Wilson *et al.*, 2004; Subramanian *et al.*, 2002; Shin *et al.*, 2006): a number of questions are asked related to the perceived aspects of the neighbourhood and the answers are usually collapsed in a few indicators (among the cited studies only that by Wilson *et al.* (2004) is different on this respect in that respondents were asked open ended questions on likes and dislikes concerning the neighbourhood, also in this case, however, they were eventually collapsed in a few indicators). In this work, attempts have been made, unsuccesfully, at using data driven techniques such as cluster analysis to define indicators, eventually we defined indicators heuristically.

The frequency distribution of the response variable is depicted in Figure 1 where it is seen that 82% of respondents reported no hospitalization. This is to be expected working with hospitalization data referred to the general population; it is worth noting that it does not inform us whether an excess of zeroes exists with respect to the traditional Poisson distribution assumption. In fact, we are not interested in the marginal distribution of the response variable, which is represented here, but on the conditional distributions estimated by the model. Suitability of a zero-inflated distribution will emerge from an analysis of the results of the fit.

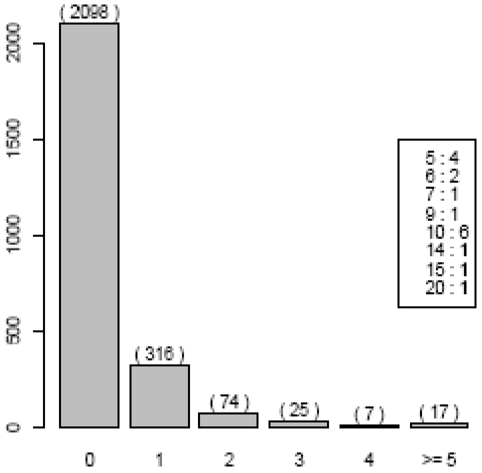

Figure 1 – Frequency distribution of the number of hospital admissions for RSA (Randomly Selected Adult), in the box the frequencies of number of hospitalizations of RSA with 5 or more hospitalizations (in addition, 82 missing observations are present).

TABLE 1

Relevant variables in L.A.FANS. Body mass index is the ratio between self reported weight (in kg) and squared height (in meters); per capita income is given by the total income divided by the number of cohabitants (it is to be noted that this variable is censored since it is the sum of censored variables)

Name	n. levels	description (levels, 1-level for dichotomic)
nhosp	num	Number of hospital admissions in the 24 months preceding interview (mean: 0.33; min: 0; max: 20)
age	num	Age of respondent (mean: 41.13; min: 18; max: 89)
bmi	num	Body mass index (BMI) of respondent (mean: 26.25; min: 17.48; max: 40.39)
proincome	num	Per capita income within family (mean: 14157.08; min: 0.00; max: 190000.00)
gender	2	gender (male)
race	5	race (latino, white, black, asian/pacific, native/other)
empl	4	employment status (unemployed (not recent), never employed, unemployed (recent), employed)
welfareinc	2	income from welfare (yes)
house	3	status house (owned, rented, other)
edu	3	education (less, high, college)
marstatus	4	marital status (married, living with partner, neither, both)
rsoc	2	having a regular source of care different than relatives and friends (yes)
res.stab	2	residential stability (moved since less than 5 years)
		Previous diagnoses[a]
cld	2	diag. of chronic lung disease
excweight	2	diag. of excess weight
depress	2	diag. of major depression
cancer	2	diag. of cancer/malignancy
emotional	2	diag. of emotional problems
hbp	2	diag. of high blood pressure
diabetes	2	diag. of diabetes
ha	2	diag. of heart attack
chd	2	diag. of coronary heart disease
artrrheum	2	diag. of arthritis or rheumatisms
asthma	2	diag. of asthma
mentalloss	2	diag. of loss of mental ability
learndis	2	diag. of learning disorder

[a]Diagnoses variables are non null if the interviewed answered positively to the question 'Have you ever been diagnosed...'.

TABLE 2

Relevant variables related to neighbourhood in L.A.FANS

Name	n. levels	description (levels, 1-level for dichotomic)
		Variables concerning informal social control[a]
hangout	2	neighbours do something if kid hangs out
graffiti	2	would do something if kid does graffiti
Disresp	2	would scold kid if showing disrespect
inf.soc.ctrl		index of informal social control[b]
		Variables concerning social cohesion[c]
closeknit	2	this is a close knit neighbourhood
willhelp	2	people are willing to help neighbours
getalong	2	neighbours generally get along[d]
sharevalues	2	people in neighbourhood share same values[e]
trusted	2	people in neighborhood can be trusted
cohes.trust		index of social cohesion and trust[f]
		Variables concerning safety in neighborhood
safe	4	how safe is to walk around alone (1=completely safe to 4=extremely dangerous)
robbed	2	household has been robbed or suffered vandalism in the neighbourhood (0=no to 1=yes)
		Other variables describing neighborhood
neigh.satisf	5	degree of satisfaction with the neighborhood (1=very satisfied to 5=very dissatisfied)

[a] All but the last are coded as 1='very likely'; 2='likely'; 3='unsure'; 4='unlikely'; 5='very unlikely' in the original coding, they are dichotomized as 'unlikely'=0='unlikely' or 'very unlikely'; 'likely'=1='very likely' or 'likely'; response 'unsure' was ignored as a missing value.

[b] The (non weighted) sum of the dichotomized variables concerning informal social control.

[c] All but the last are coded as 1='strongly agree'; 2='agree'; 3='unsure'; 4='disagree'; 5='strongly disagree' in the original coding, they are dichotomized as 'Agree'=1='strongly agree' or 'agree'; 'Disagree'=0='disagree' or 'strongly disagree'; response 'unsure' was ignored as a missing value.

[d] Variable has been given the opposite sense here than in L.A.FANS questionnaire (original question was 'neighbors generally don't get along').

[e] Variable has been given the opposite sense here than in L.A.FANS questionnaire (original question was 'people in neighbourhood don't share same values').

[f] The (non weighted) sum of the dichotomized variables concerning social cohesion and trust.

3. METHODS

Conceptually, we use an asymmetric model involving the number of hospitalizations occurred in the 24 months preceding the interview (Y) as the response variable and a selection of possible determinants as the explanatory variables (x_h). We consider generalized additive models (GAM) to analyse separately the, possibly non linear, effect of each covariate on the response. Non linear contributions are estimated by spline functions whose degree of smoothness is decided by generalized cross validation.

Being Y a frequency, the traditional model for it would be based on the Poisson distribution

$$P(Y_i = y) = \frac{\mu_i^y}{y!} e^{-\mu_i} \tag{1}$$

and on the logarithmic link function between the parameter and the linear predictor, so that, if $x_{h,i}$ (with $h= 1, ..., H$ and $i=1, ..., n$) is the observed value of the h covariate on the i-th unit,

$$\log(\mu_i) = \alpha_0 + \sum_{h \in H_s} g_h(x_{h,i}) + \sum_{h \in H_l} \alpha_h x_{h,i} \tag{2}$$

where $g_h(\cdot)$ are spline functions. The effects of covariates indexed in $H_s \subset \{1,..., H\}$ are modeled non linearly, those indexed in $H_l \subset \{1,..., H\}$ are modelled linearly ($H_s \cap H_l = \varnothing$ and $H_s \cup H_l \subset \{1,..., H\}$).

The Poisson assumption may be too restrictive for real count data, a common extension is the Zero Inflated Poisson model (Lam *et al.*, 2006) that is, one assumes that

$$Y_i = Z_i W_i \tag{3}$$

where Z_i is 0 with probability π_i and 1 with probability $1-\pi_i$ and $(W_i | Z_i=1) \sim$ Poisson (λ_i), meaning that

$$P(Y_i = y) = \pi_i I(y = 0) + (1 - \pi_i)\frac{\lambda_i^y}{y!}e^{-\lambda_i} \tag{4}$$

Covariates may affect either the parameter π_i and/or the parameter λ_i through suitable link functions, the logistic and the logarithm functions respectively in this work, so we get the two linear predictors

$$\text{logit}(\pi_i) = \beta_0^\pi + \sum_{h \in H_s^\pi} g_h^\pi(x_{h.i}) + \sum_{h \in H_l^\pi} \beta_h^\pi x_{h.i} \tag{5}$$

$$\log(\lambda_i) = \beta_0^\lambda + \sum_{h \in H_s^\lambda} g_h^\lambda(x_{h.i}) + \sum_{h \in H_l^\lambda} \beta_h^\lambda x_{h.i} \tag{6}$$

where all symbols are to be interpreted analogously to equation (2) ($H^\pi{}_s \cap H^\pi{}_l = \varnothing$ and $H^\lambda{}_s \cap H^\lambda{}_l = \varnothing$, while the other couples may have, pairwise, non empty intersections). Lam *et al.* (2006) recently proposed a method based on approximating the smooth functions by piecewise linear functions and on using the sieve maximum likelihood approach to obtain estimates to perform a semiparametric analysis within a ZIP assumption. We prefer the approach of Rigby and Stasinopulos (2005), which is based on the spline functions representation of smooth functions and the penalized likelihood approach to obtain estimates. This latter approach is in fact, to our knowledge, more widely used and tested. In practice, estimation is made using the package gamlss (Stasinopulos and Rigby, 2007) in R (R Development Core Team, 2005).

The use of a ZIP model implies greater flexibility but, on the other side, interpretation of results is a bit harder. In fact, in a ZIP model the total effect of a variable, say x_{h*}, on the expected number of hospitalizations is a combination of its effects on the parameters $\boldsymbol{\lambda}$ and $\boldsymbol{\pi}$, leading to

$$E(Y_i \mid \mathbf{x}_i) = (1-\pi_i)\lambda_i = \left[1 - \text{logit}^{-1}\left(\beta_0^{\pi} + \sum_{h \in H_s^{\pi}} g_h^{\pi}(x_{h.i}) + \sum_{h \in H_l^{\pi}} \beta_h^{\pi} x_{h.i}\right)\right] \times$$
$$\times \exp\left(\beta_0^{\lambda} + \sum_{h \in H_s^{\lambda}} g_h^{\lambda}(x_{h.i}) + \sum_{h \in H_l^{\lambda}} \beta_h^{\lambda} x_{h.i}\right). \qquad (7)$$

The result of such a combination is not obvious and, moreover, the shape of the function $s(x_{h^*})$=E(Y| x_{h^*},x_{-h^*}), also depends (due to the non linearity of the link functions) on the values of the other covariates. For this reason, in order to get a glance of the dependence of Y on x_h we compute E(Y| x_{h^*},x_{-h^*}) for a grid of values of the effect of x_{h^*}. In practice, we compute for all observed units i the quantities

$$v_i^{\pi} = \sum_{h \in H_s^{\pi} \setminus \{h^*\}} g_h^{\pi}(x_{h.i}) + \sum_{h \in H_l^{\pi} \setminus \{h^*\}} \beta_h^{\pi} x_{h.i} \qquad (8)$$

$$v_i^{\lambda} = \sum_{h \in H_s^{\lambda} \setminus \{h^*\}} g_h^{\lambda}(x_{h.i}) + \sum_{h \in H_l^{\lambda} \setminus \{h^*\}} \beta_h^{\lambda} x_{h.i} \qquad (9)$$

and consider, for some values $q \in [0; 1]$, fixed empirical q-quantiles $v^{\lambda}_{([qn])}$ and $v^{\pi}_{([qn])}$ (where $[qn]$ is the integer part of qn). These values are then substituted in equation (7) to get

$$s_q^*(x_{h^*}) = [1 - \text{logit}^{-1}(\beta_0^{\pi} + I_{H_s^{\pi}}(h^*) g_{h^*}^{\pi}(x_{h^*}) + I_{H_l^{\pi}}(h^*) \beta_{h^*}^{\pi} x_{h^*} + v_{[qn]}^{\pi})] \times$$
$$\times \exp(\beta_0^{\lambda} + I_{H_s^{\lambda}}(h^*) g_{h^*}^{\lambda}(x_{h^*}) + I_{H_l^{\lambda}}(h^*) \beta_{h^*}^{\lambda} x_{h^*} + v_{[qn]}^{\lambda}) \qquad (10)$$

where $\mathrm{I}_K(k)$ is an indicator function which is one if $k \in K$ and zero otherwise.

An alternative model one may consider is the Negative Binomial model, which is more flexible than the Poisson model (but not nested), the distribution of Y is then

$$P(Y_i = y) = \frac{\Gamma(y + 1/\sigma_i)}{\Gamma(y+1)\Gamma(1/\sigma_i)} \frac{(\mu_i \sigma_i)^y}{(\mu_i \sigma_i + 1)^{(y+1/\sigma_i)}} \qquad (11)$$

in which $\log(\sigma_i) = \gamma_0^{\sigma}$ and

$$\log(\mu_i) = \gamma_0^{\mu} + \sum_{h \in H_s^{\mu}} g_h^{\mu}(x_{h.i}) + \sum_{h \in H_l^{\mu}} \beta_h^{\mu} x_{h.i} \qquad (12)$$

is the linear predictor for μ.

Model comparison for variable selection is based on standard criteria: Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and residual deviances comparison.

To assess model adequacy we check normality of the randomized residuals, that is, the quantities

$$r_i = (1-u_i)\hat{F}_i(y_i - 1) + u_i\hat{F}_i(y_i) \tag{13}$$

where u_i are independent and identically distributed uniform random variables on [0,1], $\hat{F}$ is the Poisson, ZIP or NB distribution function with parameters equal to the estimated values (so for example in the ZIP case $\hat{F}_i(y) = \mathbf{F}(y;\hat{\pi}_i,\hat{\lambda}_i)$ where $\boldsymbol{F}$ is the d.f. of the ZIP). In any case randomized residuals are, if the model is correct, normally distributed.

4. RESULTS

In section 4.1 we report the results we got using ZIP model, in section 4.2 we briefly explore whether a simpler model – Poisson or Negative Binomial – fits well to the data.

4.1. *ZIP model*

Our model selection strategy is first to choose the most relevant among physiological characteristics of the individual, then among the socioeconomic and sociodemographic ones and finally among those concerning the neighbourhood. Choice of candidate variables for inclusion is based on previous experiences accrued in the literature.

In Table 3 we report the AIC, BIC and deviance values relevant for model comparisons. The procedure is incremental; in the *i*-th line we compare by AIC and BIC the current model, which involves all the variables selected up to step *i*, and the model obtained applying the *i*-th modification: this is actually applied (and hence the current model for step *i+1* is the one resulting from the modification) if it leads to a better AIC or BIC value than the simpler model and if the coefficient of the variable which is added is significantly different from zero at 5% level. It must be kept into account the fact that each variable has missing values for different units, so in order to do a fair comparison we must estimate both models on the same dataset (the largest one having no missing observations for the relevant variables). (It is to be noted that the inclusion of the quantities in Table 3 corresponds to the inclusion of a set of dummy variables when the quantity is a categorical variable; in this case the selection of significant coefficients may lead to the inclusion of only part of these dummy variables, that is, to an alternative definition of the factor levels.)

The ZIP model we start from (M_0) includes the main physical characteristics: age, body mass index (BMI) and gender; in particular, it includes a non linear function of age and a dummy variable for gender in both linear predictors, while a non linear function of BMI enters only the linear predictor for π.

TABLE 3

Pairwise comparisons of ZIP models for successive additions of variables from base model M_0 *(including age, gender and BMI) to final model* M_1 *(including variables in bold face in the table)*

Cathegories in the CF				AIC		BIC		Deviance	
		n	d.f.	w/out	with	w/out	with	w/out	with
Physical characteristics	+age+gender+BMI	2343	16	-	3061.12	-	3153.3	-	3029.1
	+D_1	2336	35	3058.63	2868.83	3150.7	3070.3	3026.6	2798.8
	+D_2	2336	28	2868.83	2992.48	3070.3	3153.6	2798.8	2936.5
	+D_3	2336	21	2992.48	2989.2	3153.6	3110.1	2936.5	2947.2
	+race	2336	25	2989.2	2920.66	3110.1	3064.6	2947.2	2870.7
	-g(age)+age	2336	21	2920.66	2925.2	3064.6	3046.1	2870.7	2883.2
Socioeconomic characteristics	**+g(proincome)**	2295	23	2875.82	2870.47	2996.3	3002.5	2833.8	2824.5
	+empl	2295	25	2870.47	2819.7	3002.5	2963.2	2824.5	2769.7
	+welfare.inc	2283	26	2797.18	2797.15	2940.5	2946.2	2747.2	2745.2
	+house	2291	29	2818.09	2820.5	2961.5	2986.9	2768.1	2762.5
Sociodemographic characteristics	**+edu**	2265	27	2791.33	2790.53	2934.5	2945.1	2741.3	2736.5
	+marstatus	2265	28	2790.53	2777.46	2945.1	2937.8	2736.5	2721.5
	+rsoc	2261	29	2776.3	2774.16	2936.6	2940.1	2720.3	2716.2
Neighborhood	**+res.stab**	1712	29	2120.43	2119.75	2272.9	2277.7	2064.4	2061.7
	+safety	1450	30	1908.62	1899.82	2061.7	2058.2	1850.6	1839.8
	+inf.soc.ctrl	1302	31	1690.83	1689.96	1846	1850.3	1630.8	1628.0
	+cohes.trust	1118	31	1503.48	1504.58	1654.1	1660.2	1443.5	1442.6
	+i.s.c & c.t.	1046	32	1404.09	1397.59	1552.7	1556.1	1344.1	1333.6
	+neigh.satisf	1046	40	1397.59	1380	1556.1	1578.1	1333.6	1300.0
	-I	1046	31	1380	1368.99	1578.1	1522.5	1300	1307

D_1: set of all diagnoses variables (see Table 1);
D_2: set of those diagnoses which are less correlated with age (excess weight, depression, cancer, emotional disorder, chronic lung disease, asthma, loss of mental ability, learning disorder);
D_3: set of those diagnoses which are significant in the model (that is, excess weight, depression, cancer, emotional disorder and chronic lung disease);
-g(age)+age stands for the replacement of the non linear contribution of age with a linear one;
i.s.c & c.t stands for the set of those variables related to informal social control and cohesion trust (listed in Table 2) having an estimated coefficient significantly different from 0 at 5%;
I set of variables whose coefficients is not significantly non null.

Following, we first add physical, socioeconomic and sociodemographic characteristic and then neighbourhood characteristics. The effect, in terms of AIC, BIC and deviance, of the inclusion of the above covariates is summarized in Table 3. Previous diagnoses are included since they may act as a mediator between the outcome and the determinants. We remind in Table 3 of the cathegories to which the determinants belong.

The perception of a more dangerous neighbourhood is associated with a higher mean of the number of hospitalizations, while the fact that a household has actually been robbed or has suffered a vandalism has an effect not significantly different from zero.

Informal social control and Social cohesion and trust are introduced in the model either through two indicators or through two sets of dichotomized variables (see above). Both features are not significant in model terms when indicators are used, on the contrary, if single items are considered, two of them, precisely 'getalong' and 'sharevalues' (Table 2) are significant and both with a protective effect.

Neighbourhood satisfaction is measured by a categorical variable having five levels. This is either an indirect measure of the quality of the neighbourhood and a measure of the degree to which the respondent likes the neighbourhood he lives in. In both cases, we expect a low satisfaction to be associated with a higher number of hospitalizations. Model findings are difficult to interpret, a higher average number of hospitalizations is estimated for people answering ‘neutral’ and ‘very dissatisfied’ (which, however, constitute only 6.8% of the sample).

The model originated from the above selection procedure is then stripped of those variables which, despite leading to a lower AIC/BIC when included, have, in the final model, an estimated coefficient non significantly different from zero at 5% level. This model is called M_1 in what follows. The estimated coefficients of the linear components of the final model are reported in Table 4, Figure 2 depicts the non linear contributions to the linear predictors and Figure 3 depicts the effects of relevant variables on E(Y), computed as explained in equation (10). Diagnostics for the model (right panel of Figure 4) show a satisfactory fit. In particular, the comparison of the normal probability plot of randomized residuals of the final model and that of residuals of the base model (left panel of Figure 4) clearly shows an improvement.

TABLE 4

Estimated coefficients (and their standard erros in parenthesis) for the linear components of the linear predictors of the models#M_1 *(ZIP)*,#M_2 *(Poisson)*, M_3 *(Negative Binomial) (′ denotes significance at 0.05, ″ at 0.01, ‴ at 0.001)*

Cathegories in the CF		M_1		M_2	M_3
		λ	π	μ	μ
	(Intercept)	-0.4052	-2.46625‴	-0.51	-0.22092
		(-0.49576)	(-0.70819)	(-0.41868)	(-0.59483)
Physical characteristics	age	0.01488‴	-	0.001425	-0.00143
		(-0.00436)	-	(-0.00376)	(-0.00537)
	gender=male	-0.20874	-	-0.08275	-0.32228
		(-0.18676)	-	(-0.13328)	(-0.18067)
	d.cld	0.43405″	-	0.644366‴	0.703936′
		(-0.15065)	-	(-0.18107)	(-0.30186)
	d.exc.weight	0.51566‴	-	0.272046	0.206823′
		(-0.14901)	-	(-0.14614)	(-0.21476)
	d.depress	0.48049″	-	0.915369‴	1.07146‴
		(-0.15409)	-	(-0.19388)	(-0.29544)
	d.cancer	-	-1.64512′	0.313476	0.636713
		-	(-0.70349)	(-0.21001)	(-0.32742)
	d.emotional	-	-0.90944′	-0.21804	-0.12977
		-	(-0.41451)	(-0.20985)	(-0.31054)
	race=native/other	2.76703‴	-	2.36435‴	2.183599‴
		(-0.16296)	-	(-0.22758)	(-0.51248)
Socioeconomic characteristics	empl=employed	-	1.76584‴	-1.15078‴	-1.122182‴
		-	(-0.30828)	(-0.12808)	(-0.165605)
Sociodemographic characteristics	edu=college	-1.1606‴	-2.24915‴	-0.24561	0.008907
		(-0.21879)	(-0.48547)	(-0.16456)	(-0.206754)
	marstatus=neither	-	0.69069″	-0.30207″	-0.447153″
		-	(-0.25804)	(-0.11629)	(-0.161664)
Neighborhood	getalong=1	-0.40496′	-	-0.37756″	-0.380992′
		(-0.16232)	-	(-0.12954)	(-0.18264)
	sharevalues=1	-	0.72674″	-0.15234	-0.352367′
		-	(-0.26977)	(-0.11793)	(-0.160707)
	neigh.satisf=2	0.16901	0.39106	-0.08289	0.024304
		(-0.19409)	(-0.36479)	(-0.14913)	(-0.201376)
	neigh.satisf=3	1.80436‴	2.08043″	0.305088	0.309194
		(-0.27243)	(-0.79654)	(-0.30372)	(-0.437446)
	neigh.satisf=4	0.05708	0.48203	-0.30419	-0.256483
		(-0.26082)	(-0.48789)	(-0.20714)	(-0.281482)
	neigh.satisf=5	1.28446‴	1.0982′	0.582118″	0.570242
		(-0.25217)	(-0.54051)	(-0.21865)	(-0.349067)

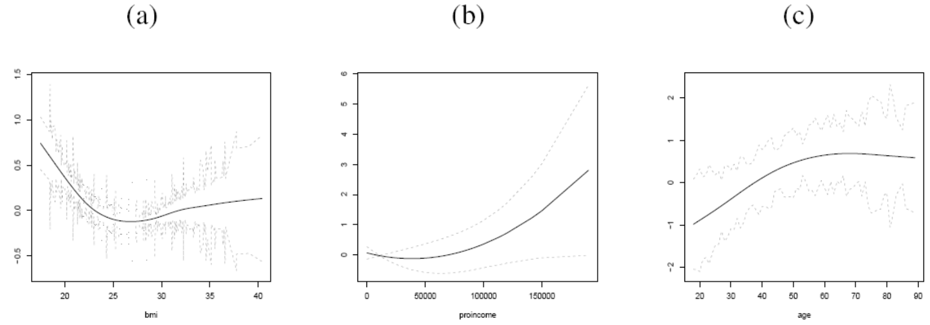

Figure 2 – Non linear contributions to the linear predictors for λ (BMI in panel (a) and income in panel (b)) and π (age in panel (c)) of the final model (M_1).

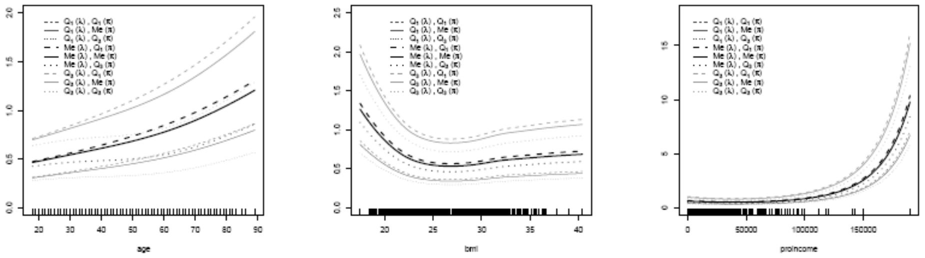

Figure 3 – Estimated conditional expectation of ***Y*** according to the final model (M_1).

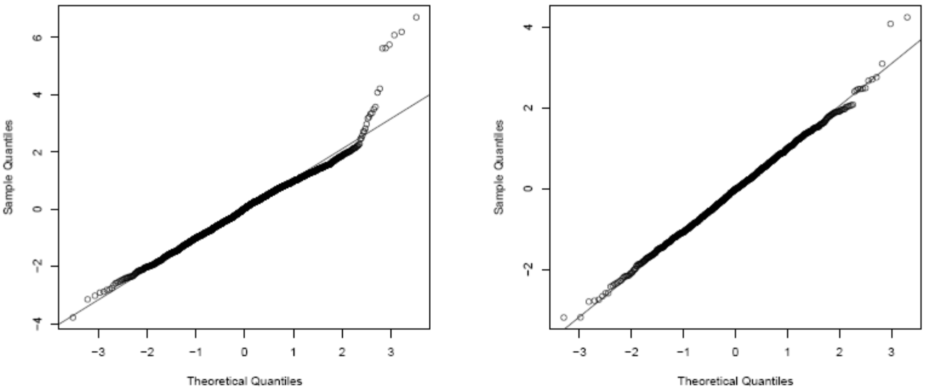

Figure 4 – Normal probability plot of randomized residuals for the base model M_0 (left) and the final model M_1 (right).

4.2. *Comparison with simpler models*

In analysing count data as the number of hospitalization which is under consideration here the Poisson distribution is the most common modelling choice. When the Poisson model fails – as is easily seen to be the case here – alternatives include the Negative Binomial (NB) and the Zero Inflated Poisson (ZIP), whose appropriateness clearly depends on why the Poisson model actually fails. In particular, the ZIP is an explicit attempt at modelling an excess of zero counts: it, in fact, postulates that the counts come from one of two regimes: either a degenerate component with unit mass in zero or a Poisson distribution. Being in presence of an excess of zero counts which can be fruitfully modelled separately is a relatively common situation in medical and public health statistics (Lam *et al.*, 2006). Such a model is also appealing on interpretation grounds since the probability of being in the zero-regime – which is explicitly estimated – may be interpreted as the probability of being in a lower risk group (subpopulation). (Clearly, this does not mean that one actually believes in the existence of two subpopulations.) The NB also allows for overdispersion with respect to a Poisson distribution but in a less specific way and does not share a similar interpretation.

It is worth noting that the ZIP distribution for Y_i differs from a Poisson distribution to the extent that π_i differs from 0 (since if $\pi_i = 0$ then $Y_i \sim \text{Poisson}(\lambda_i)$). We may then get a hint about the relevance of the ZIP model by checking how often $\hat{\pi}_i$ is significantly different from 0. We depict such a comparison in Figure 5 where we plot the estimates $\hat{\pi}_i$ ordered increasingly and, as a reference, the value of the standard error of each $\hat{\pi}_i$ multiplied by 1.96. Results show that $\hat{\pi}_i$ is, in prevalence, different from 0. This graphical display substantially resembles the kind of tests which are commonly suggested in the literature (van den Broek, 1995; Rodrigues, 2006) where, usually, the hypotheses $H_0\text{: } \boldsymbol{\pi} = 0$ is tested against $H_1\text{: } \boldsymbol{\pi} \neq 0$ by means of a score test, whose main advantage is that one does not need to estimate the more complicated Poisson model. Jansakul and Hinde (2002) consider a model in which π_i is modeled as a function of the covariate ($\log[\boldsymbol{\pi}/(1\text{-}\boldsymbol{\pi})] = \mathbf{X}\boldsymbol{\gamma}$) and propose a score test for the hypotheses H_0: $\boldsymbol{\gamma} = 0$ versus H_1: $\boldsymbol{\gamma} \neq 0$. Rather than adapting the score test to the case of predictors with smooth function we prefer estimating both model and compare them in Table 5. A test for ZIP versus Poisson can be based, since they are nested models, on the difference between the deviances (1484.8 - 1307 = 177.8) which, under M_2, has a $\chi^2_{31\text{-}23}$ distribution, thus leading to a *p*-value which is almost equal to zero.

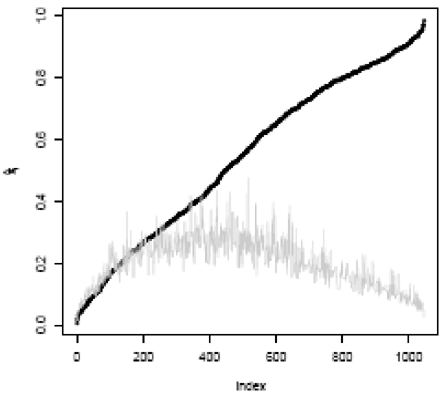

Figure 5 – Sorted estimates $\hat{\pi}_i$ (dots) in model M_1, gray line is $0+1.96 \times s.e.(\pi_i)$.

In considering the ZIP as a model alternative to the Poisson (to be considered a basic model in this context) one should keep in mind, following El-Shaarawi (1985) but also Thas and Rayner (2005) that the mere preference for a ZIP over a Poisson model (that is, the fact that the lack of fit of the Poisson distribution is due to the excess of zeros) does not imply that the former is the appropriate choice, for this reason it is worth comparing the fit also against the NB.

In order to have a fair comparison of the ZIP, the Poisson (M_2) and the NB (M_3) model, we estimate both M_2 and M_3 using as explanatory variables all variables included in the final model (in any linear predictor, in fact the conditional distribution of $\boldsymbol{Y}$ in the ZIP model depends on both $\boldsymbol{\pi}$ and $\boldsymbol{\lambda}$). Estimates of coefficients are in Table 4.

BMI and income, whose contributions to the linear predictors in Figures 6 and 3 are similar in shape, play an analogous role in the three models (the linear predictor in the Poisson and Negative Binomial models is directly related to E($\boldsymbol{Y}$), so we can compare its shape with that of E($\boldsymbol{Y}$) in the ZIP model). The contribution of age is non significantly different than a constant in the models M_2 and M_3 which may be the result of a lack of fit. The comparison of randomized residuals with a gaussian distribution (Figure 7) suggests lack of fit in the right tail for M_2, the Negative Binomial and ZIP models leading to a significant improve in that area (Figure 4). Moreover, we can compare their AIC and BIC values, such a comparison (Table 5) is in favour of the ZIP model, as already confirmed by the significance of the test previously discussed.

Thus, diagnostics and tests are consistently in favour of the more flexible Negative Binomial and ZIP models over the Poisson model, as intuition suggested beforehand. The comparison between the ZIP and NB models (based on the residuals in figures 4 and 7) leads to no clear cut conclusion.

TABLE 5

Comparison of ZIP, Poisson and Negative Binomial models: M_1 *is the final ZIP model;* M_2 *and* M_3 *are, respectively, the Poisson and Negative Binomial models involving all variables included in* M_1

	d.f.	AIC	BIC	deviance
M_1	31	1368.99	1522.5	1307.0
M_2	23	1530.76	1644.7	1484.8
M_3	24	1370.99	1489.8	1323.0

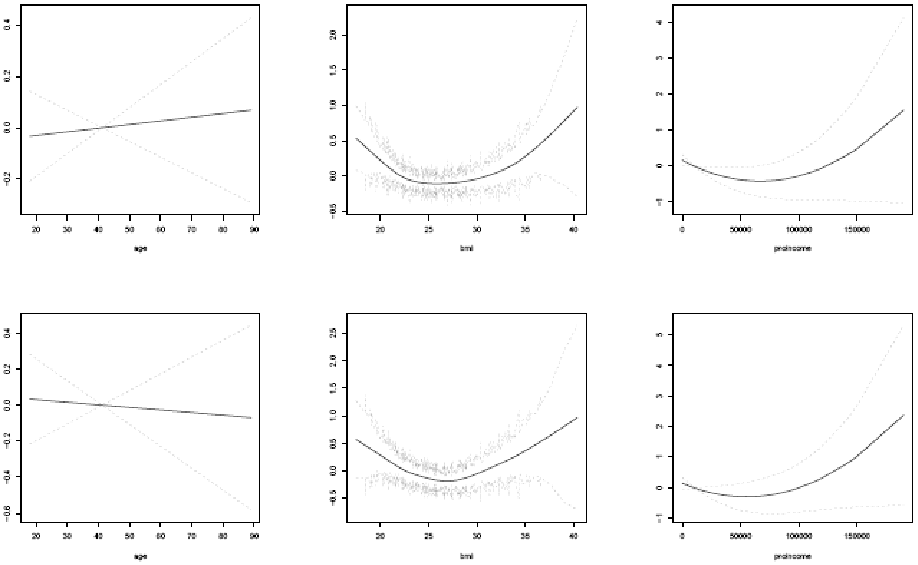

Figure 6 – Contributions to the linear predictor for μ in the Poisson model M_2 (top row) and in the Negative Binomial model M_3 (bottom row).

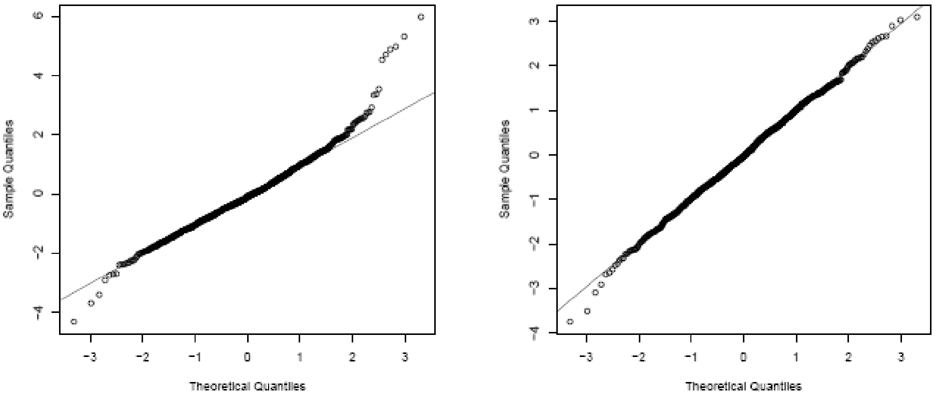

Figure 7 – Normal probability plot of randomized residuals for the Poisson model M_2 (left) and the Negative Binomial model M_3 (right).

5. FINAL REMARKS

Using data from the L.A.FAN Survey we have investigated whether some neighbourhood characteristics, measured by the perception of the individual, have a significant relationship with the expected number of hospitalizations (in two years). We have used generalized additive models which allow us to deal with non linear effects in a convenient way. This proved useful since the effects of BMI and income are clearly non linear. We also overcome to some extent the difficulties in interpreting the results from a GAM with a ZIP distribution by simulating predicted values under varying assumptions in order to reveal the relationship of interest.

A comparison has been made between Poisson, Negative Binomial and ZIP models from which it emerged that the performance of the traditional Poisson distributional assumption for count data can be greatly improved. The results are not conclusive on whether a Negative Binomial or a ZIP model is to be preferred, the latter, however is more flexible and so is preferred here. The choice of the model is relevant for our purposes since different models lead to different conclusions on the significance of the effect of the covariates (see Table 4).

It turns out relatively clearly that a high social cohesion leads to a lower hospitalization rate as shown by the fact that both the variables 'getalong' and 'sharevalues' have significant coefficients with signs implying in both cases a negative effect on the expected number of hospitalizations. Interestingly, the more general 'satisfaction' level concerning the neighbourhood does not show a clear effect.

Such results confirm the relationship of neighbourhood social environment on the health of individuals measured by the number of hospitalizations, particularly social cohesion which is, according to our results, more important than social control or public order. A strength of our evidences is that they do not depend on a specific definition of neighbourhood since each respondent refers (implicitly) to his perception, on the other hand, this is also a limitation in that it does not allow to define 'good' and 'bad' neighbourhoods.

It is also worth saying that these results are coherent with those of Shin *et al.* (2006) in their fundamental conclusion even if the modelling framework is different.

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SUMMARY

Modeling the relationship between perceived neighborhood characteristics and adult hospitalization frequencies from a cross-sectional study

Interest in the quantitative effects of neighbourhood characteristics on urban health has recently increased in social epidemiology. Such effects are mostly studied employing multilevel models based on some definition of the neighbourhood. We investigate the statistical relationship between health and the neighourhood quality as perceived by individuals, thus avoiding the need of choosing a specific definition of neighbourhood.

We use data from the Los Angeles Family and Neighbourhood Survey (L.A.FANS). We measure health status of an individual as the number of hospitalizations in the last two years. This number is related to individual carachteristics (including neighbourhood perceptions) through generalized additive models (GAM), focusing particularly on the Zero Inflated Poisson (ZIP), which is an unusual choice in this context.

We also overcome to some extent the difficulties in interpreting the results from a GAM with a ZIP distribution by simulating predicted values under varying assumptions in order to reveal the relationship of interest.

The analysis confirms that the quality of neighbourhood – as measured by perceptions of individuals – significantly relates to the health status of inhabitants – as measured by the number of hospitalizations.