SUPPLEMENTAL HEALTH INSURANCE AND EQUALITY OF ACCESS IN BELGIUM

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Summary

The effects of supplemental health insurance on health care consumption crucially depend on specific institutional features of the health care system. We analyse the situation in Belgium, a country with a very broad coverage in compulsory social health insurance and where supplemental insurance mainly refers to extra-billing in hospitals. Within this institutional background, we find only weak evidence of adverse selection in the coverage of supplemental health insurance. We find much stronger effects of socio-economic background. We estimate a bivariate probit model and cannot reject the assumption of exogeneity of insurance availability for the explanation of health care use. A count model for hospital care shows that supplemental insurance has no significant effect on the number of spells, but a negative effect on the number of nights per spell. We comment on the implications of our findings for equality of access to health care in Belgium.

Keywords: supplemental insurance, adverse selection, moral hazard, hospital spells, equality of access, health care use.

Introduction

In recent decades, many European countries have experienced a growing pressure on the financial resources of their public health care systems and a parallel increase in the importance of different forms of voluntary health insurance (Mossialos and Thomson, 2002; OECD, 2004). There are worries that this development threatens the ideal of equality of access in these countries, as voluntary health insurance seems mainly concentrated among the better-off groups in society.[1]

As emphasized by Jones *et al.* (2006), a good diagnosis of the situation requires that one is able to distinguish carefully between the different factors influencing the link between supplemental insurance and health care consumption. If there is adverse selection, i.e. if those with higher health care risks are more likely to take out supplemental insurance, it becomes crucial to disentangle this selection effect from the insurance effect.[2] While previous empirical work gives much evidence for the existence of a moral hazard (or utilization) effect, the results with respect to adverse selection are mixed. The strongest

[1] A specific example of this is the concern about the pro-rich inequity in the probability of seeing a specialist found in many European countries (van Doorslaer *et al.*, 2004) and the question of whether this phenomenon can be explained by the unequal distribution of supplemental insurance coverage (Van Doorslaer *et al.*, 2002; Buchmueller *et al.*, 2004; Rodriguez and Stoyonova, 2004; Van Doorslaer *et al.*, 2004; Jones *et al.*, 2006).

[2] In addition to the traditional "moral hazard" effect, Jones *et al.* (2006) mention a series of other "insurance" effects: risk reduction, income transfer and access. Empirically, it is impossible to distinguish between all these and we will use the terms "moral hazard" and "insurance" effect interchangeably. Some papers that have discussed the identification of the selection effect versus the insurance effect are Holly *et al.* (1998), Vera-Hernandez (1999), Schellhorn (2001), Buchmueller *et al.* (2004), Gardiol *et al.* (2005).

effects seem to be found for the free choice of deductibles in Switzerland (Schellhorn, 2001; Gardiol *et al.*, 2005). This is not very surprising, given the institutional setting in Switzerland with a strong tradition of private health insurance.

The latter point suggests an important insight, i.e. that "the nature of demand for private health insurance itself depends on the institutional context in which that insurance operates" (Harmon and Nolan, 2001, p. 135). It is indeed obvious that both the degree of adverse selection in the voluntary insurance system and the (voluntary) insurance effect on health care consumption will crucially depend on the degree of population, service and cost coverage in the public (compulsory) system and thus on the type of voluntary insurance. The wide variety of possible arrangements has been described in the international comparison reports (Mossialos and Thomson, 2002; OECD, 2004), but until now there have not been many structured attempts to formulate and test specific hypotheses which are linked to these institutional differences. In fact, a careful analysis of the institutional setting may in some cases lead to empirical predictions of an insurance effect that does <u>not</u> in the first place induce increased consumption. A careful consideration of specific institutional features is therefore essential for understanding the link between supplemental insurance and equality of access.

In this paper, we analyse the take-up and the consumption effects of voluntary health insurance in Belgium. We will describe the Belgian institutional context in the next section and we will argue that it leads to specific predictions on the effects of supplemental insurance. In the following section, we describe the data that we use to test these specific predictions. Next, we present our results for the demand of supplemental insurance and the effects of supplemental insurance coverage on health care use. We first estimate a bivariate probit model and we discuss the issue of endogeneity of supplemental insurance. We then present separate models for inpatient care and outpatient care.[3] Our data for inpatient care distinguish explicitly between the number of spells and the number of nights per spell. This allows us to improve on the single spell hypothesis, which has been common in previous research (see, e.g., the discussion in Santos Silva and Winmeijer, 2001). We discuss the predictive power of our model in an appendix to the paper. We return to the problem of equality of access in the final concluding section.

Supplemental health insurance in Belgium

Belgium has a system of compulsory health insurance, covering the entire population, which is organized through private, non-profit sickness funds.[4] The service and cost coverage within the compulsory system and the social contribution rates levied are identical for all funds. Compulsory health insurance is combined with independent medical practice. Payment is mainly fee-for-service and patients have a large degree of freedom in their choice of provider. There are no gatekeeper arrangements. Hospital care is provided either by private non-profit or by public hospitals. The system of hospital financing distinguishes between medical and non-medical services. The former are fully integrated into the system of health insurance and are covered by the sickness

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[3] To save space, we only show the results for the main models in the paper. All the other results are available from the authors on request.

[4] More detailed information on the Belgian health care system and on recent reforms can be found in Schokkaert and Van de Voorde (2005).

funds. Here also, remuneration is mainly fee-for-service. Perhaps due to the dominance of fee-for-service (in addition to the relatively large number of providers per capita), there are hardly any waiting lists.

At the same time, the Belgian system is characterized by large out-of-pocket payments, covering overall about 20% of total health expenditures. These out-of-pocket payments consist of official co-payments, health care items not included in the compulsory cover, and extra-billing. There are only few supplemental insurance policies available, which cover the official co-payments. However, the Belgian government introduced social protection mechanisms for the poor and the sick, the most important being a "maximum billing" ceiling, linked to income.

Compared to most other countries, the coverage of the compulsory insurance package is very broad, including e.g. many dentistry items and care in nursing homes for the elderly. The most important items not included in the compulsory cover are orthodontics, some new or less necessary pharmaceuticals, some physiotherapy and non-traditional therapies such as acupuncture and homeopathy. Patients can buy supplemental insurance for these treatments, but its importance remains rather limited.

Supplemental insurance is mainly relevant with respect to extra-billing ("supplements" in the Belgian terminology). Extra-billing plays an important role in hospital financing. On top of co-payments, patients can be charged a part of the price of the materials used. Mainly those opting for a single room can also be charged room and fee supplements. Physicians who do not subscribe to the officially negotiated fees are allowed to raise supplements irrespective of room choice for all patients with the exception of some vulnerable socioeconomic groups. While average co-payments per hospital stay in a single room in 2003 were between €150 and €200, supplements were on average above €800.[5] Supplemental ("hospital") insurance covers these costs – and in addition usually the co-payments and supplements in the ambulatory sector, if they are linked to the stay in the hospital. This "hospital insurance" is by far the most important type of supplemental health insurance in Belgium and the only one analysed in this article.

Both sickness funds and private insurers provide supplemental insurance. In the private sector, both group contracts and individual contracts are offered. The private market share in supplemental health insurance has remained rather limited and private insurers focus on the higher-income market segment. According to Berghman and Meerbergen (2005), supplemental insurance by the sickness funds and by private insurers covered in 2001 – the year of our data – about 2.35% and 0.65% of total health care expenditures, respectively. However, since 2001, the importance of supplemental insurance has certainly grown.

It should be clear that this institutional background will influence both the coverage of the supplemental health insurance and its impact on health care use. As mentioned before, there are hardly any waiting lists and patients with and without supplemental insurance are treated in the same hospitals. Supplements in hospitals are strictly regulated for patients in two-person and in common rooms and it can reasonably be expected that most patients in single rooms have supplemental insurance. While a stay

[5] More information about supplements in Belgium can be found in De Graeve *et al.* (2006).

in a single room will undoubtedly be more comfortable, there is no empirical evidence that it will also imply a larger consumption of health care or a better quality of care – in any case, if there is an effect, it must be rather due to differences in provider behaviour than to reactions by patients on price differences. Moreover, given the broad coverage of the compulsory system, we would only expect minor effects of supplemental insurance in the ambulatory sector – mainly for the few items, which are not covered, and perhaps for ambulatory treatment related to a hospital stay. We will analyse whether these predictions are confirmed by the data.

Data

Our data come from the Health Interview Survey (HIS)[6] in 2001, a Belgian health survey that was set up by the Scientific Institute of Public Health. The HIS collects information on supplemental hospital insurance for all adults in the sample through an oral interview. The design of the interview allowed for the specific Belgian institutional context, thus increasing the adequacy of the answers. This is a significant improvement over existing surveys. We decided to focus our analysis of the take-up at the individual (and not at the household) level, because health status is supposed to be a crucial variable and can be defined adequately only at the individual level.[7] We therefore omitted from the sample the respondents that were still going to school, because the supplementary insurance question did not apply to them. We lost additional

[6] More information on the HIS can be found in Demarest *et al.* (2002).

[7] For the analysis of the determinants of health care consumption, we constructed a variable at the individual level indicating whether the individual or a family member has supplemental health insurance for hospitalization. All common supplemental insurance policies in Belgium include coverage of household members.

observations due to item non-response in the independent variables. However, the share of individuals with supplemental hospital insurance (62.40%) in our estimation sample (n = 5349) hardly deviates from that in the total sample.[8]

We will now summarize the data on health care consumption, on individual (non-health) characteristics and on individual health. A short description of the variables and summary statistics for the estimation sample are given in Table 1. For categorical variables, we indicated the reference category with an asterisk.

Table 1 about here

The HIS contains information on utilization of the general practitioner (GP), the specialist, emergency department, dentist, prescribed and non-prescribed drugs, and hospital care.[9] Visits to day centres are not included in the definition of hospital care, but are taken up as a separate question. The information on hospitalizations allows us to define at the individual level the number of hospital spells (with a maximum of three) during the last year and the number of nights during each hospitalization.

Table 1 also summarizes the available demographic and socio-economic information. We equivalized income using the modified OECD scale that weighs the first individual with 1, subsequent individuals with 0.5 and children (defined as 13 or younger) with

[8] There is no good information to cross-validate this percentage in Belgium. Statistical analysis of the differences between the total sample and the estimation sample gives no reasons to question the assumption of exogenous sample selection.

[9] Note that in Table 1 there is additional item-non-response for some items of health care consumption.

0.3, and then categorized it into a set of six income ranges in order to allow for a flexible functional form. Some individuals qualify for lower co-payments – such preferential treatment is provided by the compulsory health insurance system to patients with a weaker socio-economic background. The HIS does not inform on job characteristics. This is unfortunate since Berghman and Meerbergen (2005) have shown that these characteristics are important for the take-up of employer-provided insurance policies. The latter are more often taken out by/provided to employees with a long-term contract, working in large firms and working in specific sectors.

One of the main strengths of the Belgian HIS is the large battery of questions on health status. We do not use the information related to acute conditions, since these most probably do not influence the decision to take up supplemental insurance. First, we use self-assessed health[10] and a dummy indicating whether the individual suffers from a chronic illness or is handicapped. In addition, the HIS contains detailed information on the type of chronic disease suffered by the respondent. We experimented with different possibilities to make use of that information and at the end decided to include the 38 diseases as separate dummies.[11] The detailed information on specific conditions gives interesting insights into the pattern of health care consumption and the correlation

[10] Since the number of respondents in "very poor health" is less than 0.5% of our sample, we pooled this group with the respondents in "poor health".

[11] We did not have enough information to classify the diseases in different severity classes. Simply using the number of diseases induces a huge loss of information, even if it is introduced in a non-linear way (or through a set of dummies representing ranges of the number of diseases).

matrix shows that there is no problem of multicollinearity.[12] Second, we calculated the body mass index based on the available information on height and weight. We construct four regions of the body mass index (see e.g. Garrow, 1992): an index between 18 and 25 indicates regular weight, while (>=25) <18 indicates (over-) underweight, and >=30 indicates obesity. Third, the survey includes the ten questions of the SF-36 physical functioning score – in which higher values correspond to better physical functioning.[13] Experimentation with different empirical specifications suggested that it was informative to divide the 0-100 range in three sub-ranges (0-33, 33-66, 66-100), for which we defined separate dummies.

Who takes up supplemental health insurance? A bivariate probit model

Let us first look at the take-up of supplemental health insurance. In the next section, we will analyse in more detail the effect of supplemental insurance on health care use. However, to get a better insight into the issue of the endogeneity of insurance status for the explanation of health care use, we present in this section the results of a bivariate probit model that jointly models the uptake of supplemental insurance and the probability of at least one night in the hospital (see e.g. Holly *et al.*, 1998). Table 2 shows the univariate partial effects, i.e. the change in the absolute probability of having supplemental insurance/at least one hospital night if a dummy takes the value 1 compared to 0.

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[12] The highest correlation coefficient between any two health variables is 0.35, and the large majority of correlation coefficients is below 0.1.

[13] The questions on the other SF-36 domains were not included in the HIS.

Table 2 about here

The first column gives the results for the take-up equation. The RESET-test for the insurance equation has a p-value of 0.28, which rejects the alternative hypothesis of misspecification (Peters, 2000), and we found no indications of heteroskedasticity using a univariate probit model with multiplicative variance function. To test the robustness of our findings, we also estimated the model with all kinds of interaction effects included and we experimented with different sets of health variables. These sensitivity analyses did not lead to significantly different results.[14]

Let us now turn to the interpretation of the results. First, we find that among the demographic variables, only age, being single without children and being a non-EU member are relevant determinants of supplemental insurance. Compared to the reference age category of 40–44, persons aged between 50 and 70 are more likely to have supplemental insurance. This finding seems to be demand-driven, whereas the decline in insurance coverage for the 70+ (compared to those between 50 and 70) might result from exclusion restrictions in insurance policies or from higher prices offered to the elderly. Unsurprisingly, singles are less likely to have supplemental insurance and the same holds for non-EU citizens.

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[14] We also investigated the predictive power of the insurance equation by analysing the percentage of correct predictions in the sample and by implementing an out-of-sample forecasting exercise along the lines of Jimenez-Martin *et al.* (2002). The latter was based on 100 random subdivisions of the sample in a training (80%) and a forecast sample (20%). The model performs well and we found no evidence of over-fitting.

Second, there are strong socio-economic differences. Individuals with a university and higher education degree are more likely, and individuals with no or primary education are less likely to have supplemental insurance. The results suggest that the relationship is non-monotonic, i.e. individuals with a university degree are less likely to have supplemental insurance than individuals with a higher (non-university) education degree. For equivalent income, a similar pattern is found, i.e. insurance take-up is associated with higher income, but again the pattern is non-monotonic. This non-monotonicity at the top is hard to explain, but should not detract from the main conclusion that there is a clear socio-economic gradient in the take-up of supplemental insurance. This is confirmed by the findings for the occupational groups. Employees are more likely than any other occupational category to have supplemental insurance.[15] Among the other categories, we observe in decreasing order the retired, the self-employed, the sick, the others not working and the unemployed. The finding for the self-employed is reasonable since – compared to some employees – they have to finance their insurance policies privately. The lower degree of risk pooling due to the absence of collective contracts probably implies higher insurance premiums. Finally, whether an individual is eligible for reduced co-payments has a negative effect on take-up.

Third, the results with respect to health and lifestyle variables are mixed. Compared to individuals in good self-assessed health, individuals in very good health are less likely

[15] Given the relative importance of employer-financed supplemental insurance, this finding was to be expected. However, there is in Belgium no reliable information available about the number of insured employees or about the percentage of policies that is paid for by employers.

to buy supplemental health insurance, which may point to some adverse selection. However, individuals in fair and (very) poor health are also less likely to take out insurance. Moreover, and more importantly, except for two specific indicators of chronic diseases, none of the other health indicators is significant at the 5% level. This does not necessarily imply that there is no adverse selection at all. First, despite the richness of the observable health information available, there may be some unobservable heterogeneity in health status left.[16] Second, the (a priori positive) effect of the lower health status may be offset by the (negative) effect of the pricing and selection behaviour of the insurers (see e.g. Shmueli, 2001). Third, other unobservable factors such as risk awareness may also play a role in the take-up decision. We think, however, that the lifestyle variables included (e.g. the positive effect of practicing sport and the negative effect of smoking) partly capture inter-individual differences in health and risk awareness.

Summarizing our results, we find only weak evidence of adverse selection and much stronger evidence for socio-economic inequalities in take-up. This is well in line with what could be predicted based on our description of the Belgian institutional setting, characterized by the very broad coverage of the compulsory system and by the (relative) luxury character of the items covered by supplemental insurance. One does not need supplemental insurance to be treated well when ill or to avoid waiting lists. However, for patients who can afford it, taking supplemental insurance may lead to a more comfortable stay in the hospital at a lower cost.

[16] Note, however, that the health information in the model is much richer than the information that is available to the insurers when deciding about policies and premiums.

We estimated the bivariate probit model to test for the endogeneity of the availability of supplemental insurance. The estimate for the correlation coefficient ρ in Table 2 shows that we find no evidence of such endogeneity. To get a better insight into this issue, we reestimated the model while imposing different exclusion restrictions in the equation for the probability of at least one night in the hospital.[17] The results for the included coefficients in the latter equation remain virtually the same with different sets of exclusion restrictions – and are almost identical to the results obtained with a single univariate probit. The sole specification for which we do reject the hypothesis of exogeneity is the one in which we include all regressors in the insurance equation and <u>only</u> hospital insurance in the equation on the probability to be hospitalized – and in that case the insurance effect is negative. As soon as we include <u>one</u> health variable (e.g. self-assessed health) in the probability to be hospitalized, any sign of endogeneity disappears.

We do not comment in detail on the results in Table 2 for the probability of spending one night in the hospital, as we will present the results for a more detailed model of health care use in the following section.

Supplemental insurance and health care use

In the first subsection, we analyse inpatient care consumption with a rich model that distinguishes between the number of spells and the number of nights per spell. In the

[17] As shown by Wilde (2000), we do not need these exclusion restrictions to identify our simple recursive model.

second subsection, we analyse the results for the categories of outpatient care that are available in our data. Correcting for endogeneity is not trivial in the count models that we use and all the results in this section are derived under the assumption that the dummy on supplemental health insurance at the family level can be seen as an exogenous independent variable. The results in the simpler model of the previous section suggest (in our view convincingly) that this exogeneity assumption does not invalidate our results. Apart from these statistical results, an additional argument for this claim is that, compared to other econometric work in this area, we use very rich information on the health status (and the lifestyle) of our respondents.

Inpatient care

The HIS informs on the number of spells and the number of nights per spell during the last year. To the best of our knowledge (Pohlmeier and Ulrich, 1995; Deb and Trivedi, 1997 & 2002; Gerdtham, 1997; Gurmu, 1997; Deb and Holmes, 2000; Schellhorn *et al.*, 2000; Gerdtham and Trivedi, 2001; Jiménez-Martín *et al.*, 2002; Riphahn *et al.*, 2003; van Doorslaer *et al.*, 2004; Van Ourti, 2004; Winkelmann, 2004; Bago d'Uva, 2005 & 2006), the literature on the determinants of the number of contacts with the medical sector has until now only focused on modelling the total number of contacts/nights without distinguishing between the spells. The most popular models are two-part and latent class count data models, or combinations of both. The former models assume a single spell, whereas the latent class models only distinguish between so-called "high"- and "low"-users. A notable exception is Santos Silva and Windmeijer (2001), who propose modelling strategies to account for multiple spells if only the total number of contacts/nights is known. Since we observe the number of spells and the number of nights per spell directly, however, we can model the individual decision process more explicitly. This may be important, since it can be argued that the decision on the number of occasions to go to the hospital (i.e. to "start" a spell) is different from the decision on the number of nights per spell, in that the patient has much less decision power on the latter than on the former.

More specifically, we stick to the popular independence assumption of two-part models, but account for spells, i.e. we assume that the data generating process of the number of spells is independent from the data generating process of the number of nights per spell. We further assume that the data generating process of the number of nights per spell is similar for each spell and independent between spells (see further for additional argumentation). Both independence assumptions enable us to estimate the number of spells and the number of nights per spell separately, rather than jointly, which is easily seen from the conditional density:

$$
\begin{aligned}
f\left(n_{is}\right) &= P\left(s_i = 0\right)^{1\left(s_i=0\right)} \cdot \prod_{k=1}^{\infty} \left\{ P\left(s_i = k\right) \cdot \left[\prod_{l=1}^{k} P\left(n_{il} \left| n_{il} > 0\right.\right)^{1\left(s_i=l\right)} \right] \right\}^{1\left(s_i=k\right)} \\
&= \underbrace{\prod_{k=0}^{\infty} P\left(s_i = k\right)^{1\left(s_i=k\right)}}_{number\ of\ spells} \cdot \underbrace{\prod_{k=1}^{\infty} \left[\prod_{l=1}^{k} P\left(n_{il} \left| n_{il} > 0\right.\right)^{1\left(s_i=l\right)} \right]^{1\left(s_i=k\right)}}_{number\ of\ nights\ per\ spell}
\end{aligned}
\tag{1}
$$

where we have for ease of exposition not explicitly accounted for conditioning on explanatory variables. n_{is} denotes the number of nights individual i spends in the hospital during spell s, s_i is the number of spells, $1(.)$ is an indicator function.

To analyse the *number of spells*, we use the negative binomial regression model.[18] It is well known that the conditional mean and variance of the number of spells are then given by

(2) $$E\left(s_i \mid y_i;\alpha\right) = \exp\left(y_i^{'}\chi\right)$$

(3) $$V\left(s_i \mid y_i;\alpha\right) = E\left(s_i \mid y_i;\alpha\right)\left[1+\alpha E\left(s_i \mid y_i;\alpha\right)\right]$$

where y_i is a vector of explanatory variables, χ its associated parameter vector, and α is the variance of the gamma distributed random component. Equation (3) shows that the conditional variance is allowed to be larger than the conditional mean – a commonly observed characteristic of health care data – if $\alpha > 0$ and $E\left(s_i \mid y_i;\alpha\right) > 0$. If $\alpha = 0$, the conditional mean and variance are equal and the model reduces to the Poisson regression model. We are not interested in the estimates of the parameters χ as such, but in the effect of the determinants y_i upon the number of spells s_i. We derive these effects by taking the exponent of the coefficients of the dummy variables as these give the proportional change in the number of spells if the dummy goes from zero to one.

The second variable, i.e. the *number of hospital nights per spell*, can only take strictly positive and integer values. We therefore analyse this variable with the truncated at zero negative binomial regression model. Analogous to the analysis of the number of spells,

[18] We did not correct for censoring in the number of spells at 3 as this only concerns 44 individuals (less than 1% of the sample). Nor did we correct for censoring in the number of hospital nights during the last spell (i.e. ongoing hospitalizations during the time of the interview) since this only concerns 24 spells, i.e. less than 4% of the total number of spells.

we present the estimation results in the form of exponentiated coefficients, which can be interpreted as the proportional increase in the *untruncated* number of nights.

The estimation results are shown in Table 3. The second column gives the results for the number of spells; the third column gives the results for the number of nights per spell. In both cases, we introduced a dummy indicating whether the individual was living in a household with at least one member having supplemental insurance (ins_family). As mentioned before, all common supplemental insurance policies in Belgium include coverage of household members. Recall that utilization refers to general and psychiatric hospitals, but excludes hospital spells for deliveries. The RESET-tests did not point to misspecification (Peters, 2000) and the estimates of α show that the (truncated) negative binomial model is preferred to the (truncated) Poisson model. Again, we experimented with different ways of including the health information and we tested for the significance of all kinds of interactions, with special attention for the effect of gender. These interaction effects turned out to be unimportant.[19]

Table 3 about here

Let us now look at the results for the number of spells in the second column. First, the effect of the socio-economic and demographic variables is rather weak. Education, income and nationality do not matter for the number of spells. The retired have more

[19] Possible explanations for the insignificance of the gender interactions are (a) that all pregnancy related aspects are excluded from our data; and (b) that the cell sizes for the very old, for which one might expect larger differences between the sexes, are rather small.

spells (which might explain the slightly surprising pattern for the age effects) and occasional smokers have less spells.[20] Second, the health variables are very significant in explaining the number of hospital spells. Having a chronic illness, or a poor level of self-assessed health, increases the number of spells and the same is true for 'worse physical functioning' as measured by SF-36. The results for the specific chronic diseases stand to reason and show that the strongest (positive) effects on the number of spells are found for individuals with kidney problems, cancer, stroke, bile problems or wrist fractures. Third (and most importantly), the number of hospital spells is not related to whether the individual or one of his/her family members has supplemental health insurance for hospitalization.

Let us now turn to the estimation results for the number of nights per spell in the third column of Table 3. We included in the model dummies for the second and third spell (the first spell is the reference category). These dummies are jointly insignificant, which gives some justification (i) for our assumption of independence between the data generation process of the number of spells and the number of nights per spell, and (ii) for assuming that the data generating process of the number of nights per spell is similar for each spell. Health indicators are the most important determinants of the number of nights. Although the general overall health indicators (self-assessed health and BMI) are explaining little, the more refined health indicators (like SF36) and the indicators of specific chronic diseases are crucially important and show an interesting pattern with

[20] It is not easy to interpret this latter effect. It may point to some socio-economic inequality in the use of hospital care or it could be seen as an indication that we did not control sufficiently for unobservable heterogeneity in patient health.

relatively longer stays for patients with liver problems, depression, stroke and other arthritis. The age effects are rather imprecisely estimated. While the income effect is not really smooth, it suggests shorter spells for patients with incomes above 80 000 BEF a month (about €2 000).

Our most striking result is the strongly <u>negative</u> effect of having a supplemental insurance on the number of nights per spell. This negative effect might be due to unobserved heterogeneity in health, leading to types of admissions with a shorter expected length of stay for individuals that have a supplementary insurance. Yet, the effect of insurance status hardly changes (and does not increase in absolute value) if we omit all the health information from the estimated model. An alternative hypothesis is that patients with a supplementary insurance (generally richer and better informed about the health care system), express a desire for a shorter length of stay. In that case, a shorter stay in single rooms may be good for the reputation of the hospital among the groups concerned.[21] Since we have no direct information about possible differences in the quality of treatment, it would be dangerous to derive from this any conclusions about a higher intensity of care in one-person rooms. We return to the issue of quality in the conclusion. However, whatever the interpretation of the negative effect, our most important finding is that there is <u>not</u> even the slightest indication of moral hazard in the form of an <u>increase</u> in the number of days spent in the hospital. Remember that this is not surprising in the Belgian context, in which the supplemental insurance only covers luxury services and the outpatient treatment after having left the hospital.

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[21] Note in this respect that many hospitals have a shortage of one-person rooms, and therefore no financial incentives to keep their patients for a longer period.

We focused in this section on the model in which the number of spells and the number of nights per spell are modelled separately. This model allows for the richest interpretation. In the appendix, we briefly compare its predictive power to that of a two-part model and a one-equation negative binomial regression model.

Outpatient care

Let us now have a look at the effect of supplemental insurance on outpatient care consumption. This allows us to test explicitly whether the specific predictions derived within the Belgian institutional setting hold in our data. We estimated negative binomial regression models for the number of visits to the emergency department and the dentist, and for the number of spells in a day centre. For visits to the GP and for the number of prescribed drugs, we estimated a two-part model consisting of a probit model and a truncated at zero negative binomial regression model (Negbin0), which fitted the data considerably better. For specialist care and non-prescribed medicines, the negative binomial model was outperformed by a two-part model consisting of a probit and a truncated at zero Poisson model (Poisson0). The estimated models included all explanatory variables that were taken up in Table 3, but for reasons of space, we show in Table 4 only the results for the supplementary insurance status. As for inpatient care, we assume that this insurance status can be treated as exogenous.[22]

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[22] We checked the relevancy of this assumption through the estimation of a set of bivariate probit models, each time with a different outpatient health care category as the dependent variable in the use equation. As soon as health variables were introduced, the assumption of exogeneity of insurance status could not be rejected in any of these models.

Table 4 about here

The results in Table 4 can easily be explained with the Belgian institutional background in mind. There is no effect on visits to a GP or to a specialist. These are covered in the compulsory system and there are no waiting lists, while supplemental insurance only exceptionally covers co-payments. There is no effect on the consumption of non-prescribed pharmaceuticals either, which indeed are not covered by most hospital insurance policies. Supplemental insurance has a positive effect on dentistry – remember that orthodontic treatment is only incompletely covered in the compulsory system. There is also a positive effect on the use of prescribed drugs (for which the co-payments usually are covered by hospital insurance, if the consumption is linked to a stay in the hospital). The lower (non significant) tendency to go to an emergency department and the higher tendency for the use of day centres are in line with the attitude towards the hospital system that also resulted in the shorter spells that were found in Table 3.

Conclusion

When analysing the effects of supplemental health insurance, it is essential to take into account the overall institutional background of the health care system. Both the take-up of supplemental insurance and the (supplemental) insurance effect on health care consumption crucially depend on the specific features of the public (compulsory) system. Simplistic international comparisons may therefore be highly misleading. This general idea is confirmed by our results for Belgium, a country in which the compulsory system has a very broad coverage, where there are no waiting lists in the public system and where supplemental insurance (at least until now) does not buy better health care quality. Moreover, supplemental insurance mainly relates to extra-billing, applied to patients who opt for a single room in the hospital.

This institutional setting leads to specific predictions that are corroborated in our empirical analysis. There are only weak indications of adverse selection in the take-up of supplemental insurance, but there is a strong socio-economic gradient. Moreover, a count model for hospital care that explicitly accounts for the number of spells shows that supplemental insurance has no effect on the number of hospital spells and a significantly <u>negative</u> effect on the number of nights per spell. The latter result is in line with the finding of socio-economic stratification in supplemental insurance and in the ensuing choice of rooms. The results for outpatient care also confirm the theoretical predictions: no effect on the number of visits to the general practitioner or the specialist; a positive effect on dentistry (including orthodontics, which are not covered in the compulsory system); and a tendency to go for a qualitatively better “use” of the hospital sector (more visits to day centres).

What can be said then about the link between equality of access and supplemental insurance? While the strong socio-economic gradient in take-up suggests that there might be a problem, supplemental insurance has hardly any significantly positive consumption effects. As an example, in Belgium the social gradient in supplemental insurance can most probably not explain the pro-rich inequity in the use of specialist care. This finding is directly linked to the broad coverage of the compulsory system. At the same time our results suggest that a decline in the degree of that coverage with a parallel increase in the coverage of the supplemental system, would lead to a sharper socio-economic inequality of access to health care if the present social gradient in the take-up of supplemental insurance remains. Moreover, our results concerning the length of hospital stays raise subtle questions about socio-economic differences in the quality of treatment. At this stage, we have no indications that the quality of medical treatment depends on the type of room and hence *de facto* on the socio-economic group (van de Glind *et al.*, 2007). However, what is the relative importance of medical and non-medical factors in defining quality? Is length-of-stay a quality indicator? Moreover, how to define what should be included in the compulsory coverage and what can be left to private decisions? While our results are not at all conclusive in this regard, the Belgian experience suggests that such more subtle questions should also be considered when analysing the growing importance of supplemental insurance.

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APPENDIX

We have focused on the interpretation of the use of inpatient care applying a model in which the number of spells and the number of nights per spell are modelled separately. This model is closer to the real world decision processes than its most obvious alternatives (a two-part model consisting of a probit and a truncated negative binomial model; and a one-equation negative binomial regression model) and therefore allows for a more relevant interpretation. One could wonder, however, about the statistical fit of these different models.

As far as we know, there is no easy statistical test available to compare these models based on the log likelihood. The main reason is that the two-part model and the one-equation negative binomial model (where the person is the observation unit) have a lower number of observations than the spell model (where the number of nights per spell is the observational level). We therefore have focused directly on the predicted number of nights *per person*.[23] Since this can be calculated with each model for all

[23] We also performed two additional checks. First, the RESET-test indicates major misspecification for the one-equation negative binomial model (p-value is 1.03E-15). The performance along these lines is better for the two part model, but there is evidence of some slight misspecification (p-values of 0.005 and 0.002 for respectively part 1 and 2 of the two part model). The RESET-test of the second part of the spell model has a p-value of 0.201, but the first part of the spell model did not converge with the square and cube of the predicted linear index included. Second, we also checked the separate effect of each variable on the predicted number of nights per person, and the effect of both parts in the two part model and the spell model. All confirmed the underperformance of the one-equation negative binomial model and the more intuitive interpretation of the spell model. Both findings make a lot of sense as the number of nights

individuals, we are able to compare the empirical distribution functions resulting from the actual number of nights (hospnight), and those resulting from the one equation negative binomial (negbin) model, the two-part model and the spell model. The descriptive statistics in Table A1 show that (i) the one-equation negbin model performs poorly and seriously overpredicts the average number of nights; (ii) the two other models have a comparable performance; but with (iii) a slightly better fit for the spell model. The fact that the spell model only marginally improves upon the two-part model (based upon the comparison of the predicted with the actual number of nights) is not really surprising since there is only a relatively low number of individuals with more than one spell (i.e. 438 individuals have one spell, 66 have two spells and 25 have three spells) and since the sequence of the number of spells seems unimportant in explaining the number of nights per spell (remember the insignificant results for spell2 and spell3 in Table 2). In addition, comparing the predicted number of nights *per person* only considers the performance of the spell model in terms of predicting the number of nights in an entire year, whereas the spell model allows analyzing the effect of variables within a spell (which is not possible with a two-part model). All in all, the slightly better predictive performance of the spell model and the fact that it gives a more realistic description of the decision process underlying hospital nights are important arguments for using it.

Table A1 about here

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per spell should have a less skewed distribution than the positive number of nights (and is thus 'easier' to model), since the latter has by definition a higher density at large numbers of nights.

Table 1: summary statistics of variables in HIS

Variable	Description	Obs	Mean	Stdev	Min	Max
	Panel A: Dependent variables					
Supplemental hospital insurance						
ins_individual	individual has supplemental hospital insurance	5349	0,624	0,484	0	1
ins_family	at least 1 household member has hospital insurance	5349	0,690	0,463	0	1
Health care consumption – general and psychiatric hospitals, excluding deliveries						
hospspell	number of spells at hospital (1 year)	5349	0,127	0,409	0	3
nightspell	number of hospital nights per hospital spell	645	8,852	17,011	1	200
hospnight	number of hospital nights	5349	1,122	7,026	0	200
Health care consumption – outpatient care						
gp	number of times visited GP (2 months)	5243	0,899	1,451	0	20
spec	number of times visited specialist (2 months) (excluding contacts during hospitalization and day care and at an emergency department)	5171	0,426	1,169	0	24
emdep	number of times visited emergency department (2 months) (excluding contacts that resulted in hospitalization)	5139	0,032	0,198	0	5
dent	number of times visited dentist (2 months)	5079	0,269	0,887	0	20
daycentre	number of visits to a day centre (1 year)	5079	0,042	0,243	0	3
med_p	number of prescribed drugs (past 2 weeks)	5349	1,306	1,799	0	27
med_np	number of non-prescribed drugs	5349	0,457	0,868	0	19

Panel B: Independent variables (dummies)

Variable	Description	Mean
Demographic variables		
male	male	0,496
age 15-24	15 <= age <= 24	0,055
age 25-29	25 <= age <= 29	0,085
age 30-34	30 <= age <= 34	0,104
age 35-39	35 <= age <= 39	0,116
age 40-44	40 <= age <= 44 [*]	0,106
age 45-49	45 <= age <= 49	0,102
age 50-54	50 <= age <= 54	0,095
age 55-59	55 <= age <= 59	0,069
age 60-64	60 <= age <= 64	0,067
age 65-69	65 <= age <= 69	0,067
age 70-74	70 <= age <= 74	0,053
age 75-79	75 <= age <= 79	0,045
age: 80-84	80 <= age <= 84	0,018
age: 85+	85 <= age	0,016
single	single without children°	0,170
single_child	single with children°	0,031
couple	couple without children°	0,328
couple_child	couple with children° [*]	0,304
complex	complex household°°	0,168
Belgian	Belgian nationality [*]	0,941
EUmember	non-Belgian EU nationality	0,043
nonEU	non-Belgian non-EU nationality	0,017
Socioeconomic variables		

eqinc: 0-20	0 BEF<=equivalent income<20,000 BEF[†]	0,041
eqinc: 20-40	20,000 BEF<= equivalent income 40,000 BEF [*]	0,385
eqinc: 40-60	40,000 BEF<= equivalent income <60,000 BEF	0,361
eqinc: 60-80	60,000 BEF<= equivalent income <80,000 BEF	0,160
eqinc: 80-100	80,000 BEF<= equivalent income <100,000 BEF	0,035
eqinc: 100+	100,000 BEF<= equivalent income	0,018
no_primary	no or primary school	0,185
secondary	secondary school [*]	0,529
higher	higher education	0,202
university	university education	0,071
otherdipl	other diploma	0,013
employee	employee [*]	0,503
self-employed	self-employed	0,069
retired	(early) pensioned	0,248
sick	disabled or invalid	0,026
unemployed	unemployed	0,063
other not working	housework, student, not working	0,092
preftreat	reduction of co-payments	0,119
sport	practising sport	0,674
smoke_dai	daily smoker	0,252
smoke_occ	occasional smoker	0,046
smokerno	non-smoker [*]	0,702
alcohol	drinking alcohol	0,821
Health variables		
sahverygood	SAH very good	0,233
sahgood	SAH good [*]	0,525
sahfair	SAH fair	0,203
sahpoor	SAH poor or very poor	0,039
chronic	chronic illness or handicap	0,289
asthma	having asthma during last 12 months	0,045
bronchitis	idem for chronic bronchitis/CNSLD[††]	0,056
allergy	idem for allergy	0,132
sinusitis	idem for sinusitis	0,085
heart	idem for serious heart condition/myocardial infarction	0,041
hypertension	idem for hypertension	0,144
abdomen	idem for serious abdominal disorders (lasting at least 3 months)	0,032
liver	idem for hepatitis/cirrhosis of the liver/other liver disorder	0,009
kidneystones	idem for kidney stones	0,010
kidney	idem for serious kidney disorder (excluding stones)	0,005
bladder	idem for chronic bladder infection	0,018
diabetes	idem for diabetes	0,033
thyroid gland	idem for thyroid gland disorder	0,042
glaucoma	idem for glaucoma	0,023
cataract	idem for cataract	0,017
parkinson	idem for Parkinson's disease	0,003
depression	idem for depression (lasting at least 2 weeks)	0,063
epilepsy	idem for epilepsy	0,004
dizziness	idem for experiencing "dizziness with falling"	0,033
migraine	idem for migraine	0,109

skin disease	idem for serious/chronic skin disease	0,031
cancer	idem for cancer	0,018
tired	idem for long-lasting tiredness (lasting at least 3 months)	0,050
back	idem for persistent back complaints (lasting more than 3 months)/lumbago/sciatica/slipped disc	0,125
arthrosis	idem for arthrosis of knees, hips or hands	0,148
arthritis	idem for chronic rheumatism/rheumatoid arthritis of hands or feet	0,077
otherarthritis	idem for other chronic rheumatism (lasting more than 3 months)	0,040
stroke	idem for brain haemorrhage or its consequences	0,005
ulcer	idem for gastric/small intestine ulcer	0,036
bile	idem for bilestones/infection of the gallbladder	0,007
osteoporosis	idem for osteoporosis	0,039
wrist fracture	idem for wrist fracture	0,006
hip fracture	idem for hip fracture	0,003
spine fracture	idem for fracture of spinal column	0,002
prostate	idem for complaints of prostate	0,021
uterus	idem for prolapse of the uterus	0,007
other1	1 if another disease is mentioned, 0 otherwise	0,067
other2	1 if a second other disease is mentioned, 0 otherwise	0,013
bmi_018	body mass index<18 (underweight)	0,018
bmi_1825	18<=body mass index<25 [*]	0,521
bmi_2530	25<=body mass index<30 (overweight)	0,338
bmi_30+	30<=body mass index (obesity)	0,123
SF33	0<=SF-36 score<33	0,059
SF66	33<=SF-36 score<66	0,089
SF100	66<=SF-36 score<100 [*]	0,852

Note: sampling weights of the HIS were used.
[*] indicates the reference category.
°: children are household members who are 18 years and younger.
°°: a complex household is a household which cannot be attributed to one of the other groups (e.g. three adults or more).
†: 1€ = 40.3399 BEF.
††: CNSLD = Chronic non specific lung disease.

Table 2: determinants of supplemental insurance and inpatient hospital admission in Belgium in 2001 (bivariate probit)

	full model	
	dependent is ins_individual	dependent is hospnight>0
male	0,002	-0,007
age 15-24	-0,101+	0,091*
age 25-29	-0,097*	0,027
age 30-34	-0,044	0,017
age 35-39	-0,027	-0,013
age 45-49	0,001	0,020
age 50-54	0,112**	0,023
age 55-59	0,096*	0,003
age 60-64	0,211**	-0,031
age 65-69	0,115*	-0,029
age 70-74	0,009	-0,046**
age 75-79	-0,007	-0,027
age: 80-84	-0,015	-0,046*
age: 85+	-0,170	-0,040
single	-0,092**	-0,020
single_child	0,009	-0,035*
couple	-0,029	-0,034**
complex	-0,051	-0,035**
EUmember	-0,013	-0,024
nonEU	-0,219**	-0,006
eqinc: 0-20	-0,185**	-0,001
eqinc: 40-60	0,059*	-0,002
eqinc: 60-80	0,087**	-0,003
eqinc: 80-100	0,159**	-0,008
eqinc: 100+	0,039	-0,061**
no_primary	-0,107**	0,004
higher	0,104**	-0,009
university	0,071*	-0,023
otherdipl	0,105+	0,077
self-employed	-0,071+	-0,013
retired	-0,071	0,029
sick	-0,126+	-0,011
unemployed	-0,219**	-0,024
other not working	-0,161**	-0,009
preftreat	-0,087*	-0,016
sport	0,062**	0,005
smoke_dai	-0,056*	-0,023*
smoke_occ	-0,095*	-0,048**
alcohol	0,055*	0,008
sahverygood	-0,068**	-0,017
sahfair	-0,062*	0,034*
sahpoor	-0,135*	0,056+
bmi_018	0,071	0,070+
bmi_2530	0,035+	-0,001
bmi_30+	-0,033	0,021

chronic	0,004	0,035**
SF33	0,011	0,086**
SF66	0,040	0,045*
asthma	-0,017	0,012
bronchitis	-0,022	0,058*
allergy	-0,022	-0,011
sinusitis	0,002	-0,023
heart	-0,036	0,013
hypertension	-0,045	0,016
abdomen	-0,018	0,042
liver	0,087	0,119+
kidneystones	-0,017	0,094
kidney	0,177*	0,197*
bladder	0,071	-0,016
diabetes	0,076+	-0,013
thyroid gland	0,045	0,007
glaucoma	-0,050	-0,004
cataract	0,012	0,023
parkinson	-0,095	-0,032
depression	0,048	0,050*
epilepsy	0,047	0,069
dizziness	0,042	-0,004
migraine	-0,020	-0,020+
skin disease	-0,061	0,055+
cancer	0,030	0,113*
tired	0,073+	-0,006
back	0,032	-0,003
arthrosis	-0,050	0,023
arthritis	0,024	-0,011
otherarthritis	0,017	0,010
stroke	-0,096	0,170
ulcer	-0,001	0,014
bile	0,052	0,207*
osteoporosis	0,109*	0,028
wrist fracture	-0,176	0,183
hip fracture	-0,062	0,107
spine fracture	-0,208	0,050
prostate	-0,089	0,059
uterus	0,067	0,001
other1	0,003	-0,009
other2	0,122+	0,003
ins_family		-0,017
ρ	0,061	
Observations	5349	
Log likelihood	-4535	

Note: we report univariate partial effects, i.e. the change in the absolute probability of having supplemental insurance/at least one hospital night when a dummy takes 1 compared to 0 while using the average value for all other independent variables. 38 regional (district) control dummies are not reported. Sampling weights of the HIS were used. Statistical inference is based on robust covariance matrices that allow for clustering at the household level: +: significant at 10%; *: significant at 5%; **: significant at 1%; shaded area: jointly not significant at 10%.

Table 3: determinants of hospital spells and nights per spell in Belgium in 2001

	dependent is hospspell	dependent is nightspell
male	0,963	0,975
age 15-24	2,087*	0,567
age 25-29	1,283	0,391*
age 30-34	1,029	0,612
age 35-39	0,742	0,771
age 45-49	1,168	0,425*
age 50-54	1,065	0,957
age 55-59	0,729	0,377*
age 60-64	0,492*	0,990
age 65-69	0,593	0,926
age 70-74	0,400**	1,334
age 75-79	0,500+	1,250
age: 80-84	0,446+	1,029
age: 85+	0,386+	0,395
single	0,715+	1,242
single_child	0,621	1,069
couple	0,660*	0,902
complex	0,576**	0,982
EUmember	0,715	0,719
nonEU	0,854	0,741
eqinc: 0-20	0,999	0,727
eqinc: 40-60	1,074	0,658**
eqinc: 60-80	0,953	1,134
eqinc: 80-100	0,985	0,389+
eqinc: 100+	0,208*	0,229**
no_primary	1,022	1,122
higher	0,830	0,982
university	0,716	1,369
otherdipl	1,891	0,218**
self-employed	0,801	0,712
retired	1,569*	1,327
sick	1,070	1,287
unemployed	0,728	2,059+
other not working	0,899	1,327
preftreat	0,866	0,927
sport	1,068	1,211
smoke_dai	0,776+	1,139
smoke_occ	0,401**	0,921
alcohol	1,017	0,838
sahverygood	0,744	0,974
sahfair	1,458**	1,038
sahpoor	1,693*	0,916
bmi_018	1,543	1,090
bmi_2530	1,039	1,127
bmi_30+	1,175	1,270
chronic	1,517**	1,069
SF33	1,769**	2,335**

SF66	1,540*	1,443+
asthma	1,228	0,496**
bronchitis	1,508*	1,288
allergy	0,751+	0,798
sinusitis	0,817	0,863
heart	1,339	0,842
hypertension	1,267	0,655*
abdomen	1,199	1,142
liver	1,810+	2,873**
kidneystones	1,924+	0,882
kidney	3,032**	1,786
bladder	1,084	1,109
diabetes	0,761	1,041
thyroid gland	1,072	0,715
glaucoma	1,042	0,826
cataract	1,187	1,024
parkinson	0,521	1,571
depression	1,482*	2,706**
epilepsy	1,374	0,421+
dizziness	0,887	0,720
migraine	0,747+	0,859
skin disease	1,459+	0,562+
cancer	2,174**	1,124
tired	0,951	0,948
back	0,881	0,794
arthrosis	1,252	0,727+
arthritis	0,761	1,043
otherarthritis	1,195	1,853*
stroke	2,559*	4,835**
ulcer	1,292	0,853
bile	2,454*	0,939
osteoporosis	1,352	0,672+
wrist fracture	4,191**	0,115**
hip fracture	1,951	1,191
spine fracture	2,439	0,740
prostate	1,399	0,857
uterus	1,268	0,248*
other1	0,879	0,599+
other2	0,865	1,076
ins_family	0,960	0,672*
spell2		1,160
spell3		0,925
alpha	0,456**	0,787**
Observations	5349	645
Log likel	-1832	-1689

Note: exponents of coefficients (measuring the proportional change in the number of spells/nights per spell if the dummy goes from zero to one) are reported. 38 regional (district) control dummies are not reported. Sampling weights of the HIS were used. Statistical inference is based on robust covariance matrices that allow for clustering at the household level: +: significant at 10%; *: significant at 5%; **: significant at 1%; shaded area: jointly not significant at 10%.

Table 4: effect of supplementary insurance on outpatient health services in Belgium in 2001

health care category		effect of ins_family
gp	Probit	0,037
	Negbin0	1,037
spec	Probit	0,013
	Poisson0	1,055
emdep		0,783
dent		1,278*
day centre		1,512*
med_p	Probit	0,026
	Negbin0	1,099*
med_np	Probit	-0,009
	Poisson0	1,002

Note: These effects are obtained in a model where all the variables are included that are also in Table 3. We report partial effects of supplementary insurance (the absolute change in the probability when the dummy takes 1 compared to 0 while using the average value for all other independent variables) for the probit models and exponents of coefficients (measuring the proportional change in the number of visits/contacts/number of drugs if the dummy goes from zero to one) for the other models. Negbin0 refers to a truncated at zero negative binomial regression model and Poisson0 refers to a truncated at zero Poisson model. Sampling weights of the HIS were used. Statistical inference is based on robust covariance matrices that allow for clustering at the household level: +: significant at 10%; *: significant at 5%; **: significant at 1%; shaded area: not significant at 10%.

Table A1: negative binomial model versus two-part model versus spell model of hospital nights in Belgium in 2001

	hospnight	Negbin	two-part model	spell model
average	1,122	4,167	1,275	1,231
max	200	5085,410	237,316	218,458
min	0	0,003	0,002	0,005
stdev	7,026	64,267	5,429	5,117
coef of var	6,261	15,423	4,259	4,158
skewness	13,661	47,699	17,522	15,190
kurtosis	269,922	2831,417	502,676	345,379
percentile 1	0	0,014	0,019	0,026
percentile 5	0	0,037	0,057	0,066
percentile 10	0	0,056	0,084	0,100
percentile 25	0	0,116	0,163	0,178
percentile 50	0	0,261	0,315	0,330
percentile 75	0	0,736	0,781	0,741
percentile 90	1	2,630	2,031	1,855
percentile 95	5	7,356	4,340	4,162
percentile 99	26	55,956	17,871	18,002

Note: Sampling weight of HIS were used.