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Publication date
2009

Document Version
Submitted manuscript

UvA ECONOMETRICS

Discussion Paper: 2009/03

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The deductible in health insurance: do the insured make a choice based on the arguments as intended by the policy makers?[1]

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November 2009

Keywords: demand for health care, health insurance, deductibles, count data model, copula estimation technique.

Abstract
This paper analyzes the decision to accept a deductible or not in the case of health insurance in the Netherlands. A simultaneous model, specifying both the the choice for a deductible and the number of doctor visits, is estimated on Dutch data from 2007. The results indicate that the choice for a deductible does not depend on the health status of individuals and the expected demand for health care in case of having or not having decided for a deductible. As a result, the main argument of the Dutch government for the introduction of a deductible, making people more aware of the health costsm, appears not to be relevant.

1 All ML-routines used in this paper are available on request. All estimations are carried out with R (free software, for information see http://www.r-project.org/). In this paper use is made of data from the CentERdata Databank.

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1. Introduction

Health care expenditures in western economies are ever rising and are becoming a growing concern for both governments and residents. The burden to cover the costs invokes all the inventiveness of policy makers to come up with new ideas intended to decrease the rate of growth of these expenditures. The reason for the growing consumption of health care is threefold (cf. Bago d'Uva and Jones (2009), Okunda and Murthy (2002), and Chiappori, Durand and Geoffard (1998) for more thorough discussions): (1) the demographic shifts towards the geriatric age groups, (2) the ongoing development in medical care technology, and (3) the existence of large-scale health insurance schemes. The first cause is beyond the control of governments. The second cause can be tackled but conflicts with the general consensus that technological improvements should be encouraged and is not very popular for elective reasons. The last argument offers the best opportunities to reduce, or, more realistically, slow down, the health care expenditures, especially in countries with publicly provided or financed health care system or insurance. Bago d'Uva and Jones (2009) give an extensive overview of the different methods European governments have used to slow down or even reduce health costs. All these methods boil down to addressing the well known phenomena of moral hazard and adverse selection. One popular measure to make sure that the insured bear part of the risk is the introduction of deductibles (cf. van Kleef, van de Ven and van Vliet (2009)). It is an attempt to provide an incentive to reduce health risks and unnecessary health care demand. At the heart of the arguments for the introduction of a deductible lies the believe of policy makers that the insured can actively manipulate their health care demand and on top of that, are also willing to do so. Of course, the introduction of deductibles might also serve an important, more down to earth, objective. Budget cuts, i.e. partly shifting the financial burden from the government to the public, might be the ultimate driving force and invoking public awareness might only be window dressing.

This paper addresses the choice for the size of the deductible in the Dutch situation. In the Netherlands residents are obliged to obtain basic health insurance, although is offered by private companies. The government sets the rules and the insurance companies make the best out of it within the framework set. From January 1st 2006 the health insurance system of the Netherlands system was reformed and a no claim of €255 became compulsory. On top of that, individuals had the option to accept a deductible. It is this voluntary deductible we will analyze in this paper. The questions we would like to answer is what are the determinants for the choice of accepting an additional deductible and does expected health care demand influence this choice. Those people that expect to make use of the health care system more frequently will be less inclined to accept a deductible. Apart from their health status, individuals will also consider, or at least that is what policy makers expect them to do, the difference in health care system usage under the regimes of having chosen or not having chosen for a deductible. If this difference in usage is large, people will me more likely to accept a deductible since it might bring them financial gain by means of a reduction of health insurance premium. Adding this variable to the analysis is what is new in this paper compared to the earlier empirical contributions on the relation between health care demand and insurance choices. It will bring about, that we have to model both the choice for a voluntary deductible or not and health care demand and we have to take account of the potential correlation between both of these choices. Both moral hazard and adverse selection predict a positive correlation between insurance coverage and health care demand (cf. Chiappori, Durand and Geoffard (1998)).

Our paper is structured as follows. Section 2 provides a brief discussion of the economic issues involved and briefly reviews the literature on related research. In section 3, the econometric model is discussed. Section 4 contains information on the data and in section 5 the empirical results are presented. The last section concludes.

2. Economic considerations and previous research

The relation between the deductible in health insurance and the demand for health care is clear cut, at least in theory. Deductibles will diminish the moral hazard problem. People will not make use of the health care system for every itch or other bagatelle but are believed to think consciously about their health care utilization choices because it involves direct financial repercussions. In the Netherlands a no claim of €255 per year was introduced for every individual older than 17 on January 1st, 2006.[3] On top of that, individuals had a free

3 The no claim was organized as follows. Individuals without any health insurance claims during a certain year received €255 at the end of the year. If the total claim exceeded zero but was lower than €255, individuals were refunded the difference between €255 and their claim. People with a claim exceeding €255 received nothing. See van Kleef, Beck, van de Ven and van Vliet (2008) for more information on the obligatory Dutch basic health insurance system. As such, a no claim implemented in this manner does not differ structurally from a deductible, apart from the fact that in the case of the no claim individuals are only aware of their health costs afterwards and in the case of deductibles they are aware of it directly. This is the reason why the Dutch system changed again on January 1st, 2008. At that point the no claim was replaced by a regular deductible of €150.

choice to increase their financial risk by an annual deductible of €100, €200, €300, €400 or €500, while at the same time reducing their health insurance premium. The aim of this paper is to analyze this choice, especially in relation with differences in the health demand of those opting for a deductible and those who do not.

First, let us consider the effect of the existence of a no claim of €255 alongside a potential deductible. Apart from a higher financial risk there appears to be no effect. Dutch legislation states that first the no claim has to be charged in case of medical expenses and if it is completely used up, the deductible will be charged. Due to the way the no claim is organized, cf. footnote 3 for details, we can consider it to be a compulsory deductible. The choice for an additional voluntary deductible will me made on the same arguments as in the case that a no claim did not exist, although the higher financial stakes will make a choice for a deductible less likely than in the case that no no claim would exist.

Second, on what factors does the choice for a voluntary deductible depend? In his analysis on the same problem using Swiss data, Schellhorn (2001) reports effects of age, subjective and objective health indicators and regional differences. A direct impact of differences in the demand for health care for those individuals that opted for a deductible and those who did not, is not taken into account, however, whereas this directly relates to one of the reasons of existence of deductibles. If health care utilization is free, or at least perceived to be free, the demand will be higher. This suggests that some of the demand is not necessary and that people can directly manipulate their demand if that is advantageous to them. The choice for a high deductible might indicate either one of two things. Either the person is very healthy or has a high degree of command over his health care demand. The first point hints at an adverse selection problem and we need to take this into account. The second point needs to be viewed not only from the financial perspective. Clearly, removing ones uncertainty about the status of health might be part of individual preferences. Risk aversion, especially if the risk is concerned with health, might be a very important factor in individual choices on health demand. As a result, the effect of the command over health care demand, might be smaller than policy makers believe and the choice for a deductible or not, might above all be made on the basis of the perceived health status of the decision maker. Nonetheless other factors, like personal characteristics such as age, gender, income or whether the household is able to keep money in reserve, might play a role in the choice for a deductible or not, as well. The financial personal characteristics might be especially important because in the Dutch situation the maximum size of the deductible is relatively low and in reality even lower that the maximum voluntary deductible of €500 suggests. This is due to a lower insurance premium for higher deductibles. Because of the relatively small amount of money involved, many households might be inclined to take a gamble especially if they expect limited health care system usage and have sufficient financial reserves. To get an idea about the reduction in the health insurance premium the individual has to pay, consider Table 1.

- insert Table 1 -

Table 1 lists the monthly premiums of ten, arbitrarily chosen, insurance companies for the most basic package offered by the company. Such a package covers the costs of basic health care (physicians, drugs, specialists, hospitalization etc.) but not dentists, physiotherapists, other kinds of therapists, etc. The average reduction of the premium for a €500 voluntary deductible compared to a no-deductible contract is about 19%. As a result, the actual financial risk in the case of a deductible of €500 is only €293 on average.

To formalize things, denote the tendency to accept a deductible by D_i, where i indicates the individual under consideration. If D_i is low, individual will be less inclined to accept a deductible, if it is high he will be. The higher it gets, the larger the deductible chosen will be. The inclination D_i will depend on personal characteristics, say combined in a vector X_i, subjective and objective health indicators, represented by a vector H_i, and the differences in health care demand for the different sizes of the deductibles, say ΔHCD_i. We can write:

$$D_i = f(X_i, H_i, \Delta HCD_i) \quad (1)$$

The difficulty in this lies in the measurement of the differences in health care demand for different levels of deductibles. First of all, we have very incomplete information about health care demand available in our data set. The only relevant measure we have is the number of doctor visits in a certain year. Not only does this measure not fully describe health care demand but there is another problem as well. According to the Dutch legislation on health care insurance, doctor visits are not taken into account in the no claim and deductibles in order to guarantee good access to basic health care. As a result the number of doctor visits appears to irrelevant in the choice for a deductible or not. Nonetheless, we believe that the number of doctor visits is still a good proxy for health care demand because of two reasons. First, a contact with a physician is always the first step that has to be taken in order to get access to the Dutch health care system, except in the case of a real emergency when individuals can go, or usually will be brought, to a hospital directly. Second, although going to see a doctor is free of charge, its consequences are not and we expect that individuals will take this last fact into account in their decisions. Doctors often prescribe drugs or refer to specialists or therapists and the costs involved with this will be charged to the individual or his insurance company. A final argument is that only going to visit a physician is an independent choice made by the individual. Decisions on the options resulting from this choice, e.g. using drugs or seeing a specialist, will have to be made in accordance with the physician which makes choices no longer only individual choices and what is more the opinion of the physician will, almost always, be decisive. Given these three arguments we believe that using the number of doctor visits as a proxy for health care demand even in the present Dutch situation is perhaps a non optimal but valid procedure. The consequence of using only a proxy might be that the relevance of differences in health care demand on the decision to accept a deductible or not will be reduced. Thus, insignificance of this explanatory variable might merely reflect that we are using a bad proxy. This problem can be (partly) overcome by introducing health indicators as explanatory variables. Clearly, health status will influence health care demand and therefore the choice for a deductible. People with high health risks, are more likely to demand health care and will be less inclined to accept a deductible.

A fundamental problem is the measurement of health care demand across the different levels of deductibles the individual can choose from. What we need, is an estimate of the difference in health care demand for different sizes of the deductibles. The question is how to measure this difference and just as important, what to measure. To start with the second problem, we have six regimes: a deductible of €0, €100, €200, €300, €400 or €500. So, what sizes of deductibles should we compare? We can compare 120 (5!) different combinations and we need to combine these numbers into one measure. Instead of introducing a more complicated choice model or having to make restrictive assumptions on how to get one measure of the difference in health care demand across the regimes, we decided to keep things simple by only considering the no deductible and positive deductible options. How to measure the difference in health care demand is then obvious: simply use $\Delta HCD_i = (HCD|deductible$

> *0) - (HCD|deductible = 0)*. Clearly, this is not an efficient procedure since we do not use all information available. The empirical analysis of Schellhorn (2001) on the size of the deductibles and its relation with the number of visits to a physician, indicates that using full information (his ordered logit estimates) or only bivariate information (his logit estimates) is not consequential. The estimated effects of the explanatory variables are quite similar. On top of that we did some empirical research on this issue ourselves and we did not draw different conclusions than those presented in this paper (see section 3, for more detailed information). A final argument for using only part of the information available, is the relative low proportion of people choosing for a deductible in our sample. Only 30% (325 observations in the largest sample we used) opted for a positive deductible. The distribution across the different sizes of the deductibles is €100: 10.9% ,€200: 11.9%, €300: 4.1%, €400: 0.0%, and €500: 3.5%.

To answer the question how to measure the difference in health care demand across the two regimes left, we need to acknowledge that we can only observe the number of doctor visits under the regime chosen. What is more, in the choice for a deductible it is not the realized number of doctor visits that is relevant, it is the expected number of doctor visits that will be taken into account. If we are able to estimate the expected number of doctor visits, we can predict this quantity in both regimes and consequently we have solved our problem. The estimation of the expected number of doctor visits will be estimated on the basis of the realized doctor visits using a count model. Since the choosing for a deductible or not can be expected to correlate with the choice on the number of doctor visits we need to take potential correlations into account. In the next section we discuss how we will do that.

At this point we want to raise the question whether individuals will make a decision in this complicated way. Can we not simply assume that in his decision on taking a deductible or not, last years health care demand, in our case measured by the number of doctor visits in 2006, is decisive? To solve this issue, we will simply let the data decide. On top of the explanatory variables in (1) we will also use last year's number of doctor visits, or actually, in order to avoid simultaneity bias, the estimated individual mean of the doctor visit count as an explanatory variable. We will denote this variable by $Ey_i(2006)$ Fortunately, the data we have access to is a panel and we indeed have information on last year's number of doctor visits.[4] The number of observation will be somewhat reduced due to attrition, however. We loose 228

4 Information on the voluntary deductible is only available in the most recent 2008-wave of the panel, so we can not employ the panel character of our data.

observations. On top of that, last year's data relate to 2006 and in that year the new health insurance system was introduced and deductibles already existed in 2006. Unfortunately, no information on deductibles is available in the 2006-panel. As a result we had to ignore potential differences in health care demand, as measured by the number of doctor visits, in our estimation of the expected number of doctor visits in 2006.

Note that the explanatory variable ΔHCD_i is a key variable in our analysis. It reflects the reason why policy makers believe that deductibles are a good way to reduce the health care costs in an economy. Policy makers assume that individuals can make a conscious choice about their health care demand and that some health care can be avoided.[5] So, for some people ΔHCD_i is large in absolute value[6], indicating that some health care demand is not absolutely necessary. These people can manipulate their demand for health care if that will bring them some financial gain. For others, this might not be possible because ΔHCD_i is small (close to zero, but still negative). As a result, we expect that the variable ΔHCD_i will decrease the probability of choosing for a deductible. Good health, whether measured objectively or subjectively, will have a positive impact on this probability. This also holds for variables reflecting a good financial position of the individuals or the household the individual belongs to. From the perspective of the policy makers, ΔHCD_i should be the only factor influencing the decision on the deductible. Improper arguments like access to money reserves and health status should not play a role since it will introduce adverse effects like an increase of differences in wealth or adverse health effects since some people might be tempted not going to a doctor while it is actually necessary. Clearly, this is a rather strict interpretation. The significance of health indicators might signal that our proxy for health care demand is of poor quality. Apart from that argument, significance might also indicate an actual effect of these variables themselves.

Note that an estimated insignificant effect of ΔHCD_i on the probability of having a deductible does not indicate with certainty that the argument of the policy makers for introducing a deductible is false. Risk aversion might also lead to a insignificance of this variable. Since we do not have a measure for risk aversion we can not correct for this.

Previous research on the issue of deductibles and its relation with health care demand is not very abundant, although a huge literature on related subjects exists. Recent

5 See, van Kleef, Beck, van de Ven and van Vliet (2008) or van Kleef, van de Ven and van Vliet (2009) for an extensive recent discussion of the effect of (voluntary) deductibles on health care systems.

6 Note that due to the definition of this variable it is always nonpositive. Since we estimate a count model for both regimes we can check whether this is indeed true.

investigations on the effect of health care insurance choices on the demand for health care can be found in Hurd and McGarry (1997), Beaulieu (2002), Riphan, Wambach and Million (2003), Deb, Li, Trivedi and Zimmer (2006) and Barros, Machado and Sanz-de-Galdeano (2008). All these papers conclude that adverse selection in the purchase of health insurance exists. Some of these investigations allow for the endogeneity of variables reflecting insurance options, but none of them implement (expected) health care usage as an explanatory variable in the decision on the health insurance plan. Specific investigations on the relation between deductibles or the related issue of copayment include Mueller and Monheit (1988), Chiappori, Durand and Geoffard (1998), Schellhorn (2001) and Cockx and Brasseur (2003). The more recent paper take explicit account of endogeneity of some of the explanatory variables but again none of them include health demand across different options in the choice for insurance plan. As we argued before, we believe that taking the differences in health care usage, in our model reflected in the variable ΔHCD_i, explicitly into account, makes it possible to test whether individuals can actively manipulate their health demand, a factor policy makers appear to be convinced of. The explanatory variables used in the studies mentioned are to a large extend the same as we will use in our analysis. Age, gender, health indicators, regional dummies, financial means etc. will be used to explain the choice for a deductible or not and the number of doctor visits. Schellhorn (2001) comes closest to our investigation. He finds that a large number of variables are relevant in the choice to accept a deductible or not. In particular he finds effect of age, cultural background, level of education, health indicators, income and region of residence have a significant impact on this choice.

3. Econometric modelling

In the decision to accept a deductible in their health insurance, individuals are expected to take their health status and especially the number of times they expect to visit a doctor into account. The believe that individuals have a direct influence on the number of visits gives the argument for the introduction of deductible in health insurance and this is put forward as one of the ways to reduce health costs by governments or insurance companies. The question remains whether these factors are actually taken into account in individual decisions or whether other factors are much more important. In the latter case it is questionable whether the free choice to have a deductible or not will indeed reduce health care costs in an economy.

As discussed earlier we will assume that individuals only have a choice to accept a deductible or not. The fact that in Dutch reality, they can also choose the size of the deductible will be ignored. Individuals opt for a deductible ($d_i = 1$) if they believe that the expected net results of this option measured in money, utility or whatever else people use in their decision are higher than that of its only alternative: no deductible ($d_i = 0$). Under the usual linearity assumption we specify the difference between the net results of both options as follows:

$$D_i = \beta' H_i + \gamma(E(y_i|d_i = 1) - E(y_i|d_i = 0)) + \alpha' X_i + \varepsilon_i \tag{2}$$

The inclination to accept a deductible, D_i, is made dependent on health indicators, denoted by the vector H_i, the difference in the expected number of doctor visits (y_i) with and without a deductible and other explanatory variables that might influence the decision as collected in X_i. ε_i is an error term with zero mean and constant variance. The unknown parameters α, β and γ need to be estimated. If $D_i \geq 0$ the individual will opt for a deductible ($d_i = 1$), if $D_i < 0$, individual i will not choose for a deductible ($d_i = 0$). Clearly, those individuals having a good health, say indicated by a relatively high H_i, are more likely to accept a deductible. They are more likely not having to spend money on solving their health problems and therefore will benefit from choosing for a deductible. Consequently we expect a positive β. The expected sign of γ is negative. Clearly, $E(y_i|d_i = 1) - E(y_i|d_i = 0) \leq 0$ needs to hold. If this difference is large, individuals can influence their number of doctor visits considerably and they will be more willing to opt for saving money by accepting a deductible. Consequently, $\gamma < 0$. This effect is counteracted by risk aversion. If individuals are risk averse, the costs attached to going to a doctor more often might be offset by a utility gain. This might result in a $\gamma = 0$ or less extreme a value of γ closer to zero but still negative. As we discussed earlier, another reason for a reduced effect of health care usage might be the non optimal way we measure it. The number of doctor visits is only a proxy. If this is indeed the case, we expect a higher significance of the health indicators, since they will take over part of the effect and health indicators can be expected to relate to future health care demand.

In eq. (2) we do not observe $E(y_i|d_i = 1) - E(y_i|d_i = 0)$. We do observe the number of doctor visits but only under one of the regimes. The situation is analogous to the switching regression or Roy model (see for instance, Maddala (1983, p. 261), van der Gaag and Vijverberg (1988), or Cameron and Trivedi (2005, p. 555)). In our case the the dependent variable is a count whereas in the switching regression model it is a continuous variable. So what we have here is what we can name a switching count model:

$$y_{1i} \sim F_{1i}(\lambda_{1i}) \quad \text{observed if } d_i = 1$$
$$y_{0i} \sim F_{0i}(\lambda_{0i}) \quad \text{observed if } d_i = 0 \qquad (3)$$
$$d_i = 1 \text{ if } D_i \geq 0 \text{ and } d_i = 0 \text{ if } D_i < 0$$

where $F_{ji}(\lambda_{ji})$ is the cumulative distribution of the count y_{ji} with expectation λ_{ji} under regime j. The random variables in this model are y_{1i}, y_{0i} and ε_i and they are potentially correlated. Clearly $\lambda_{ji} = E(y_i|d_i = j)$ and as a result the model is complete. By employing the copula estimation technique, the model depicted by eqs. (2) and (3) is estimable with FIML if the exact marginal distributions are specified.[7] This method takes full account of the potential correlations between the random variables distinguished.[8] The copula estimation technique is outlined in the appendix. A full treatment of this technique can be found in Trivedi and Zimmer (2005). In this paper we will use the Gaussian or normal copula and assume Poisson or Negative Binomial distributed counts and a normal distributed ε_i. The variance of this error term can only be estimated up to a scaling factor and will therefore be put equal to 1. The Poisson distribution is the starting point of the empirical analysis of the counts. In order to allow for unobserved heterogeneity we will also consider Negative Binomially (NB2) distributed counts (cf. Cameron and Trivedi (1998, p. 71)).[9] The NB2 distribution has the Poisson distribution as a special case. If it equals 0, the distribution reduces to the Poisson. Suppose that we collect all explanatory variables of a count, say y_i, in a vector Z_i, then it is common to assume $E(y_i) = \lambda_i = exp(\beta' Z_i)$ in the case of a Poisson distributed count. If we add unobserved heterogeneity (v_i) to the expectation: $\lambda_i|v_i = exp(\beta' Z_i + v_i) = exp(\beta' Z_i)exp(v_i)$ and

7 Note that we indeed specify marginal distributions here, although parameter restrictions across different marginals will be used in some instances. In particular, note that (2) only contains one random variable (ε_i). The other elements are deterministic although the parameters in the difference in expectations are in common with parameters in (3). In (3), two different marginals are added. Even if we restrict the parameters to be equal for both count distributions, apart from the constant but including the correlations, the distributions remain real marginals.

8 Since y_{1i} and y_{0i} are not observed simultaneously, the correlation between these counts can not be estimated.

9 Alternative specifications of unobserved heterogeneity are available as well. Winkelmann (2004) uses the normal distribution for the heterogeneity term. We tried this as well but were unable to get the ML-routine to converge. Winkelmann (2004) models a correlation between an unobserved heterogeneity term in the count and the error term of a 1-0-choice decision. This can be considered a more restrictive specification than the one we use in this paper (see Van Ophem (2009) for details).

assume that $exp(v_i)$ has a gamma distribution the resulting count distribution is the NB2. If the variance of $v_{i,}$, reflected in the parameter θ, equals 0, the count distribution collapses to the Poisson again. Deb and Trivedi (2002) and Bago d'Uva and Jones (2009) use a latent class model to take account of heterogeneity and find that this gives better results than standard models employing the Poisson or the Negative Binomial distribution.[10] Since the number of observations in our data is rather limited (about 1000) we did not pursue this line of research, but we decided to use the semiparametric heterogeneity model of Heckman and Singer (1984), which can be considered as a special case of the latent class model. In this model, unobserved heterogeneity is allowed to take M values (points of support) that have to be estimated along with corresponding probabilities.[11]

In the model constituted by eqs. (2) and (3) we will estimate two correlations: the correlation between ε_i and $y_i|d_i = 0$ and the correlation ε_i and $y_i|d_i = 1$. We expect both correlations to be negative. Due to selfselection, individuals with a high demand for health care will be more likely to have a negative ε_i. Significant negative correlations therefore indicate that people indeed take account of their (expected) health care demand in their decision for a deductible or not, although the relevant explanatory variables are not observed. From the viewpoint of thee arguments for the introduction of a deductible as put forward by policy makers, a significant negative correlation signals that these arguments are important.

As discussed in the previous section, the decision to have a deductible or not might also depend on the expected number of doctor visits as such. In that case we should add an extra variable to (1) but the question is what variable? The unconditional expected number of doctor visits ($E(y_i)$) is the ideal variable but it can not be directly estimated. This problem can be sidestepped by using the linear combination $E(y_i) = P(d_i = 1)\mathrm{E}(y_i|d_i = 1) + (1 - P(d_i = 1)) E(y_i|d_i = 0)$ and to estimate the elements on the rhs separately, The resulting model will be either impossible or at least very hard to estimate. Furthermore, it is questionable whether individuals would reason in such a complicated manner especially because a much simpler proxy is available: the number of times an individual went to see a doctor last year. Still introducing this variable might involve an endogeneity problem so we prefer to use the expected number of doctor visits in the previous year. Denote this variable by: $E(y_i(2006))$. Adding this variable to the specification gives rise to the following specification:

10 Winkelmann (2005) found even better results for normally distributed unobserved heterogeneity terms. We attempted to estimate the model under this assumption but we did not achieve convergence.

11 Cf. Cameron and Trivedi (2005, p621) for more information and on the relation between the semiparametric heterogeneity and latent class model.

$$D_i = \alpha' X_i + \beta' H_i + \kappa E(y_i(2006)) + \gamma(E(y_i | d_i = 1) - E(y_i | d_i = 0)) + \varepsilon_i \quad (4)$$

κ is expected to be negative. As we will see the disadvantage of using $E(y_i(-1))$, is loosing about 21% of the observations. We estimate $E(y_i(-1))$ with a Poisson model.[12]

In reality we know more about the deductible. In our data information is available on the height of the deductible in six categories: 0 (no deductible), 100 euro, 200 euro, 300 euro, 400 euro or 500 euro. Using this more precise information would potentially improve the quality of our estimations. However, although it is not hard to imagine how to model this, simply use an ordered probit model instead of the regular probit model, two problems arise. First, we need to distinguish six regimes each with a potentially different count distribution. This will complicate the model considerably and we will probably have to rely on simulation estimation techniques in order to estimate the model with FIML. Second, what difference in expected health system usage should we use in the equation reflection the height of the deductible choice? There appears to be only the haphazard solution of comparing the without deductible expected count with the expected count of one of the other categories. We actually estimated a ordered probit model combined with the Poisson model to investigate the effect the additional information on the deductible had on the empirical results using the expectation of the expected number of doctor visits in the case of a deductible of 500 euro and only assuming different count distributions for the no deductible and positive deductible regimes where we added four dummies for the five different heights of the deductible. The empirical conclusions presented in this paper do not differ from those found in this exercise. Thus, and because of the objections raised earlier, we decided not to present the estimation results of the model employing full information on the deductible in this paper.

4. Data

The data used in this paper come from the DNB Household Surveys 2008 and 2007.[13] This panel survey is collected by CentERdata since 1993 and consists of information on about 2000 Dutch households participating in the CentERpanel. The CentERpanel is an Internet panel that reflects the composition of the Dutch-speaking population. Participants who do not

12 We rely here on the well known pseudo ML-property of the Poisson model (cf. Cameron and Trivedi, 2005, p. 668)

13 These surveys are available to investigators without charge. See http://www.centerdata.nl/.

have Internet access are provided with a Net.Box by CentERdata, allowing them to access the Internet through their televisions. Households that do not have a TV set are given one by CentERdata. Information is available on all the individual members of the households as well as combined household information. The DNB Household Survey concentrates on financial issues especially related to housing (rents and mortgages), property, debt and savings but also contains information on labor market participation, income and health. The information collected in the 2008 or 2007-survey for the larger part relates to 2007 or 2006.

From the original DNB Household Survey we first selected only the heads of households and their partner, if present. We then checked whether information on the dependent and explanatory variables was complete and deleted incomplete individual observations. To ensure independent observations, we proceeded by choosing one of the possibly two remaining household members at random. After these manipulations, 1083 observations were retained. For the estimations that use information on the number doctor visits in 2006 (cf. eq (3)) we selected the observations with information available both in the 2008 and 2007 waves: 855 observations remained (79%). Information on the deductible of the health insurance is only available in the 2008-survey.

The dependent variables in our empirical analysis are:

- d: dummy variable, the respondent has chosen for a deductible ($d = 1$) or not ($d = 0$);
- y_1: count variable, the number of doctor visits if $d = 1$;
- y_0: count variable, the number of doctor visits if $d = 0$.

Recall that either y_1 or y_0 is observed, and not both. Information on the dependent variables can be found in Tables 2 and 3.

- insert Tables 2 and 3 -

The two samples we use in our investigations are denoted by 'N = 1083' and 'N = 855'. About 24% of the respondents did not see a doctor in 2007. The average number of doctor visits is 2.24. The standard deviation, about 2.8, is somewhat higher than this number and this might be an indication that the Poisson distribution is not adequate since this distribution assumes equal mean and variance. Counts above ten are rare. The maximum reported number of doctor visits in 2007 is 40. The majority of respondents do not see a doctor more often than four times a year. About 30% of the respondents opted for a deductible. The reduction in the number of observations from 1083 to 855 appears to have only a very marginal effect on both having a deductible or not and the number of doctor visits. This suggests that the loss of some observations does not introduce a selectivity problem.

The following explanatory variables are used in the estimations:

- able to save: dummy variable to 1 if the household the respondent belongs to was able to save more than € 1500,= in the 12 months preceding the interview, 0 otherwise;
- age (scaled): age in years divided by 10;
- age^2 (scaled): square of age in years divided by 10;
- BMI (body mass index): weight (in kilograms) divided by the square of length (in meters), also known as the Quetelet-index;
- breadwinner: dummy variable equal to 1 if the respondent is person in the household with the highest income, 0 otherwise
- child younger than 7: dummy variable equal to 1 if the household the respondent belongs to contains at least one child younger than 7, 0 otherwise;
- chronically ill: dummy variable equal to 1 if the respondent claims to be suffering from chronic illness, is disabled or still suffers from the consequences of an accident, 0 otherwise;
- drinker: dummy variable equal to 1 if the respondent claims to drink more than four alcoholic beverages a day, 0 otherwise
- female: dummy variable equal to 1 for female respondents, 0 for male respondents;
- good health: dummy variable equal to 1 if the respondent claims to be in excellent or good health, 0 otherwise;
- living in urban area: dummy variable equal to 1 if the respondent lives in a very strong or strong urban part of the Netherlands, 0 otherwise;
- number of children: the number of children belonging to the respondent's household;
- partner: dummy variable equal to 1 if there is a partner in the respondent's household;
- self-employed: dummy variable equal to 1 if the respondent claims to be self employed, 0 otherwise;
- smoker: dummy variable equal to 1 if the respondent smokes cigarettes regularly, 0 for nonsmokers.

Quantitative information on the explanatory variables can be found in Table 4.

- insert Table 4 -

Again, we can conclude that restricting the sample to respondents observed in both the 2008- and 2007-survey gives very similar descriptive statistics. It appears that no selectivity is introduced by this procedure.

Some other variables were used in preliminary estimations of the model. Variables like those reflecting labor market status (full time work, part time work, being unemployed), educational level dummies, regional dummies (place of living in northern, eastern or southern part of the Netherlands), incomes (actual level and income categories) etc. did not have significant effects and it was decided to remove them from the analysis.

5. Estimation results

Table 5 presents the estimation results of the simultaneous model on deductible choice (yes or no) and the number of doctor visits where the difference in this count across the individuals that have opted for a deductible and those who did not, is only reflected in a constant: the 'deductible = 1'-variable. Clearly this is quite a restrictive assumption and in will be relaxed shortly. The difference between the first and second column with estimation results is first the number of observations and second, and this is the reason for the first difference, the inclusion of the 'Expected number of doctor visits in 2006'-variable (E*(y(2006)*). To create this variable we used the observations that were both present in the 2007 and 2008 survey, and hence we experienced some reduction of the number of observations due to attrition, and estimated a Poisson model on the number of doctor visits in 2006. The individually estimated expected values of this Poisson count were included as a regressor in the estimations. Like the variables, chronically ill, good health and BMI, this variable reflect the (perceived) health condition of the individual. A surprising result is that these health variables do not appear to have any impact on the choice for a deductible whatsoever. Not even being chronically ill has a significant effect. This insignificance might be due to multicollinearity, but this is not the case because if we delete one or more of the health indicators the remaining variables are left insignificant. Both age and age squared are strongly significant. The estimation results show a U-shaped relation which reaches a minimum at the age of about 53-54. So, the probability of choosing for a deductible decrease until the age of 54 and then starts to increase. This is a result we did not expect. In our opinion an ever decreasing probability would have been more likely, especially because of the relation between age and health. From this we can again infer that health status as such does not play a role in choosing for a deductible or not. Perhaps, the explanation of this result lies in the relation between age and having children: at the age of 50 to 55 it can be expected that children start leaving the household and thereby improving the financial position. The insignificance of the number of children casts some doubt on this explanation, however.

- insert Table 5 -

Another variable that has a significant impact on the choice for a deductible is being able to save money. Those households that can do so, are more likely to decide for a deductible. This variable is income related and reflects more or less the same thing: wealthier individuals can easily bear some limited financial risk and can therefore afford to take chances. Inclusion of income as an additional regressor led to insignificance of both income and the 'able to save'-variable. Since this last variable in our opinion reflects better whether the individual can bear financial risks and also because this variable was more significant, we decided to delete income from the specification. Females are less likely to opt for a deductible than comparable males. The model parameter γ reflects the effect of the difference between the expected number of doctor visits with and without having a deductible. It has the expected negative sign but is far from significant.

In the specification represented in Table 5 it was assumed that the number of doctor visits is Poisson distributed. With respect to the number of doctor visits, the estimation results show that the health indicators, chronically ill, good health and BMI have a significant effect on the expected number of doctor visits. The chronically ill and people with a tendency towards adiposis visit physicians more often. People that believe to be in good health go less often. No effect is found of smoking and drinking alcoholic beverages frequently. Females and the elderly, visit doctors more often. If there are young children present in the households doctors are also more frequently visited. A somewhat contradicting results is that if the individual belongs to a household with many children, he visits a physician less often. The effect of having a partner, being self-employed and living in an urban area is significant only in one of the two specifications, although all signs are negative. The individuals that opted for a deductible see a doctor less often then those that did not.

A surprising result is the insignificance of the correlation. This indicates that unobserved effects influencing the number of visits to a doctor does not contain information influencing the decision to accept a deductible or not. As discussed before, we expected a negative correlation. One of the reasons for this result might be that we treat the groups with and without a deductible too much in the same manner. Perhaps the underlying process governing the decision on the number of times to visit a doctor is completely different for these groups. This will be investigated next. A final conclusion that we want to draw on the basis of the results presented in Table 5 is that the estimation results hardly differ across the two samples used.

- insert Table 6 -

The loglikelihood values of the specifications in Table 6 indicate that it is indeed a good idea to allow for different parameters for the Poisson count distributions of the number of doctor visits. With 13 degrees of freedom the LR-statistics of 62 ('N = 1083'-sample) and 60 ('N = 855'-sample) are significant at 15 (critical χ^2-value: 27.7). If we look at the parameters estimates of the probability of choosing for a deductible, the results are very similar to those of Table 5. Neither the significance nor the size of the parameter estimates differ too a large degree. So the conclusions drawn earlier remain valid. Again we find that the difference in health care usage across the two regimes, measured by γ, and the correlations (ρ), the most important policy parameters, are insignificant. With respect to the parameters of the counts we see some differences across the groups distinguished. In particular, the effect of gender and age is much larger for the groups of individuals with a deductible. The effect of the health indicators has somewhat diminished (i.e. being closer to zero) if we compare the 'deductible = 0'-sample with the 'deductible = 1'-sample. BMI is no longer significant for the last group of observations. Drinkers who decided to have an health insurance with a deductible go significantly less often to a doctor. All in all we can conclude that the specifications in Table 6 is better than the ones in Table 5, but that still important parameters are insignificant. To extend the model further, we will now allow for unobserved heterogeneity in the doctor visit counts by using a Negative Binomial distribution instead of the Poisson (Table 7).

- insert Table 7 -

Table 7 shows that significant changes in the estimates of the model parameters occur. Three out of four estimated correlations become significant. What is more, the parameters θ are all significant indicating that unobserved heterogeneity exists.[14] Recall that the specifications given in Tables 5 and 6 are special cases of the one in Table 7 and we can conclude that this last specification outperforms the others. This is also shown by the loglikelihood values. The correlation between the error term of the deductible choice and the count in the case of not having a deductible is negative, as we expected, and large in absolute value. The positive correlation between the error term of the deductible choice and the count in case of having a deductible is unexpected, although it is only significant in one out of two cases. This positive correlation indicates that individuals with a relative higher risk of going to a doctor or more likely to opt for a deductible. This is odds with expectations but apart from this again seems to oppose the major argument of policy makers to introduce a deductible. We do not have a good economic explanation for this positive correlation, and because of that we have to discard this specification.

If we ignore this infeasible correlation we can conclude that with respect to the parameter estimates of the deductible choice equation we find basically the same results as before. Health indicators and γ do not have any impact on the choice. Age and being able to save appear to be the only significant determinants. In particular, and as we encountered before, last year's number of doctor visits does not play a role. The probability of taking a deductible decreases until the age of about 53 ('N=1083'-sample) and 47 ('N=855'-sample) and increases thereafter. As such this is similar to what we found before expect that in the smaller sample the minimum is reached earlier. People who can afford to save money are more inclined to accept a deductible. Gender no longer has a direct effect on the probability of deciding for a deductible. As before, last year's number of doctor visits does not play a role. The estimates of the count distribution are quite similar to our earlier estimates. One difference is that both the number of children or having very young children no longer plays any role in the distributions of the number of doctor visits. We find that the expectation of the count in the case of having a deductible exhibits less structure than the one related to having

14 To be more precise, the variance of the count is $\lambda_i + \theta\lambda_i^2$, indicating that the expectation of the count (λ_i) is no longer equal to the variance due to the inclusion and importance of the unobserved heterogeneity (cf. p. 62, Cameron and Trivedi (1998)).

no deductible. Age, good health, being a drinker and living in an urban area always play a role but other factors in the determination of the number of doctor visits. Chronic illness and BMI are only important if the individual did not opt for a deductible. All in all we can conclude, that despite one unexpected and two significant correlations, the estimation results with respect to both the choice for a deductible and the distribution of the count, hardly differ from the ones presented in Table 6.

- insert Table 8 -

Table 8 presents the estimation results of the semiparametric heterogeneity model with three support points for each of the two Poisson distributed counts.[15] The correlations, although positive in three out of four cases, are no longer significant. Unobserved heterogeneity seems to exist, although some of the corresponding probabilities are quite small and insignificant. In one case the interpretation of the unobserved heterogeneity component is clear. In the N = 855- sample one of the unobserved heterogeneity components is estimated as about -13 (-11.0-1.8). This indicates that there exists a group of individuals, with a size of 4-5%, within the sample of people that opted for having no deductible, that is very unlikely to visit a doctor. As we encountered before, the effect of the expected demand for health care on the choice for a deductible or not, measured by γ, is negligible from a statistical point of view. In the larger sample only one factor is significant in the choice for a deductible. Only those that are able to save money are more likely to opt for a deductible. For the smaller sample the same conclusion holds but we also find age and gender effects. The probability of opting for a deductible is larger for males and decreases up to the age of 50 and then starts to rise. These results are completely in line with the results we found before. This conclusion is also correct for the determinants of the expectation of the counts. Again, gender and the health indicators have a significant impact on the expected number of doctor visits. Drinkers that opted for a deductible visits physicians significantly less than comparable non-drinkers. Older individuals visit doctors more often.

From a statistical point of views the estimation results relating to the Negative Binomial distribution (Table 7) should be preferred to the Poisson estimates (Table 6), as can

15 We also estimated the model with two and four point of support. The model with two possible values of the unobserved heterogeneity term was clearly outperformed by the presented model: the LR-statistics is 27.2 (for the N = 1083-sample) where the critical value at 1% is 13.3 (4 restrictions). The model with four points of support hardly does better: LR < 0.1.

be simply deduces from the significance of the parameters related to the variances of the unobserved heterogeneity terms. Whether the estimates in Table 7 should be preferred to the ones in Table 8 is unclear since both specifications are not nested. Following e.g. Winkelmann (2004), we can compare them by using the Schwartz Information Criterium (SIC). We find: 5611.4 and 5645.4 (N = 1083) and 4509.8 and 4494.8 (N = 855), so the conclusion is ambiguous. Since the preferred (NB2-) model for the N = 1083-sample, has a unexplainable positive correlation, we prefer the model with the semiparametric heterogeneity.

To get insight in the magnitude of the effect of differences in the explanatory variables consider Table 9. It lists the estimated probabilities, differences in probabilities with respect to a reference individual (Δ), the estimated expected number of doctor visits for individuals with (λ_1) and without a deductible (λ_0), the differences between these two magnitudes and differences with respect to the reference individual. The reference individual is defined just below the table and the other entries of the table deviate in one characteristic from this reference. The reference individual has a probability of 0.332 to choose for a deductible. His expected number of doctor visits is 0.504 if he has chosen for a deductible and 0.768 times if he has not. Note that the expected number of doctor visits is always estimated to be larger in the case of having no deductible.

To start with the probability of choosing for a deductible, we observe an unexpected effect of age, although of course, this was already clear form the estimation results presented in Tables 5 to 8. The probability decreases until the age of about 50-60 and then starts increasing again. Given the negative relation between age and health one would expect an ever decreasing probability. An explanation might be greater wealth of older people, the decreasing number of dependent children after the age of 50, or a too restrictive quadratic specification of age. To investigate this last explanation, we added dummy variables for age categories instead of age and its square. This revealed the same pattern, however. The ability to save increase the probability of having a deductible with 10%. As we discovered before, health indicators only have a very marginal effect on this probability. The conditional expected numbers of doctor visits do show significant health effects. People that are chronically ill or perceiving not to be in good health visit doctor one time more often on average than the reference individual. As such, this increase is very modest but if we compare it with the conditional number of visits if they did not opt for a deductible, differences are much larger. The chronically ill go and see a doctor on average two times whereas not being in good health increases this number to 1.4. This shows that the expected number of doctor visits is markedly different in the cases of having or nor having a voluntary deductible. As we saw, this large difference appears to have no impact whatsoever on the choice for a such a deductible or not. Also note the effect of BMI: an increased BMI does not really increase the number of doctor visits if the person does have a deductible whereas we observe a large increase if he does not. The effect of age on the number of doctor visits is straightforward. Older people see doctors more often than younger people. Those having a deductible go less often than those who do not but it appears that the gap closes. All in all we can conclude that the expected number of doctor visits under the two regimes are markedly different, indicating that indeed individuals do react on the regime and will decide to see a doctor more often if than does not involve any direct costs. Despite of this result, we do not find an effect of this difference (the coefficient γ in Tables 5 to 8) and any health indicator, apart from perhaps age, on the probability of choosing for a deductible. In our opinion, and due to the unexpected effect of age, we should not think of age as a health indicator. If this is true, the probability of having a deductible or not is completely independent of health status. As a result the main reason for introducing deductibles in health insurance in the Netherlands, stimulating more conscious use of health care services, seems not to be play any role. At best this effect works through unobserved elements in the decision on the deductible, but a significant negative correlation was only found in the NB2-specification so this evidence is not strong. The introduction of deductibles appears to favor the wealthy and risk lovers in particular.

6. Conclusion

In this paper we analyzed the decision to opt for a deductible or not in the case of the new health insurance system in the Netherlands. In an attempt to reduce the steady increase of the nationwide health costs, the health insurance was reformed in 2006. One of the changes was the introduction of a no claim and a voluntary deductible, in order to make Dutch citizens more conscious of their health care demand and the costs it brings. In our empirical investigation we employed a number of different specifications for the count distribution and the distribution of unobserved heterogeneity but they all gave rise to the same conclusion: the objective of the policy makers is not or only very marginally met. We never found an effect of health care demand or health status and in only one specification we found a significant negative correlation between the choice for a deductible and health care demand. It appears that only age and wealth influence the choice for a deductible. Since the effect of age is U-shaped we do not believe that age acts as a health indicator. In our opinion a better explanation is that after the age of about 50, children leave the household and as a result households have more money to spend. It appears that only those who can afford to run some risk will choose for a deductible. An alternative explanation is that of risk loving. Since the size of the deductible is very modest, in particular if the reduction of the insurance premium is taken into account, it is not a big deal for some people to run the risk. This might hint at a more effective way to make people aware of health care costs: increase the deductible significantly. The risk of this measure will be that some people that can not actually afford to run the risk of a high deductible, will decide to do so anyway because of the much lower monthly insurance premium. As a consequence it is questionable whether policy makers are willing to follow this advice.

References

Bago d'Uva, T, and A.M. Jones, 2009, Health care utilization in Europe: New evidence from the ECHP, *Journal of Health Economics*, vol. 28, pp. 265-279.

Barros, P.P., M.P. Machado and A. Sanz-de-Galdeano, 2008, Moral hazard and the demand for health services: A matching estimator approach, *Journal of Health Economics,* vol. 27, pp. 1006-1025.

Beaulieu, N.D., 2002, Quality information and consumer health choices, *Journal of Health Economics*, vol. 21, pp. 43-63.

Cameron, A.C., T. Li, P.K. Trivedi, and D.M. Zimmer, 2004, Modelling the differences in counted outcomes using bivariate copula model with application to mismeasured counts, *Econometrics Journal*, vol. 7, pp. 566-584.

Cameron, A.C., and P.K. Trivedi, 1998, *Regression analysis of count data,* Cambridge University Press.

Cameron, A.C., and P.K. Trivedi, 2005, *Microeconometrics: methods and applications*, Cambridge University Press.

Chiappori, P.-A., F. Durand and P.-Y. Geoffard, 1998, Moral hazard and the demand for physician services: Firste lessons from a French natural experiment, *European Economic Review*, vol. 42, pp. 488-511.

Cockx, B., and C. Brasseur, 2003, The demand for physician services: Evidence from a natural experiment, *Journal of Health Economics*, vol. 22, pp. 881-913.

Deb, P., and P.K. Trivedi, 1997, Demand for medical care by the eldery: a finite mixture approach, *Journal of Applied Econometrics*, vol. 12, pp. 313-336.

Deb, P., and P.K. Trivedi, 2002, The structure of demand for health care: latent class versus two-part models, *Journal of Health Economics*, vol. 21, pp. 601-625.

Deb, P., C. Li, P.K. Trivedi and D.M. Zimmer, 2006, The effect of managed care on health care services: Results from two contemporaneous household surveys, *Health Economics*, vol. 15, pp. 743-760.

Heckman, J.J., and B. Singer, A method for minimizing the impact of distributional assumptions in econometric models of duration data, *Econometrica*, vol. 52, pp. 271-320.

Hurd, M.D., and K. McGarry, 1997, Medical insurance and the use of health care services by the elderly, *Journal of Health Economics*, vol. 16, pp. 129-154.

Lee, L., 1983, Generalized econometric models with selectivity, *Econometrica*, vol. 51, pp. 507-512.

Lindeboom, M., and G. van den Berg, 1994, Heterogeneity in models for bivariate survival: the importance of the mixing distribution, *Journal of the Royal Statistical Society, Series B*, vol. 56, pp. 49-60.

Madalla, G.S., 1983, Limited-dependent and qualitative variables in econometrics, Cambridge University Press.

Mueller, C.D., and A.C. Monheit, 1988, Insurance coverage and the demand for dental care, *Journal of Health Economics*, vol. 7, pp. 59-72.

Okunade, A.A., and V.N.R. Murthy, 2002, Technology as a 'major driver' of health care costs: a cointegration analysis of the Newhouse conjecture, J*ournal of Health Economics*, vol. 21, pp. 147-159.

Riphahn, R.T., A. Wambach, and A. Million, 2003, Incentive effects in the demand for health care: a bivariate panel count data estimation, *Journal of Applied Econometrics*, vol. 18, pp. 387-405.

Santos Silva, J.M.C., and F. Windmeijer, 2001, Two-part multiple spell models for health care and demand, *Journal of Econometrics*, vol. 104, pp. 67-89.

Schellhorn, M., 2001, The effect of variable health insurance deductibles on the demand for physician visits, *Health Economics*, vol. 10, pp. 441-456.

Sklar, A., 1959, Fonctions de repartitiona n-dimensions et leurs marges, *Publication de l'Institute de Statistique de l'Universite de Paris*, vol. 8, pp. 229-231.

Trivedi, P.K., and D.M. Zimmer, 2005, Copula modeling: An introduction for practitioners, *Foundations and Trends in Econometrics*, vol. 1, pp. 1-111.

van der Gaag, J., and W. Vijverberg, 1988, A switching regression model for wage determinants in the public and private sectors of a developing country, *The Review of Economics and Statistics,* vol. 70, pp. 244-252.

van Kleef, R.C., K. Beck. W.P.M.M van de Ven and R.C.J.A. van Vliet, 2008, Risk equalization and voluntary deductibles: A complex interaction, *Journal of Health Economics*, vol. 27, pp. 427-443.

van Kleef, R.C., W.P.M.M. van de Ven and R.C.J.A. van Vliet, 2009, Shifted deductibles for high risks: More effective in reducing moral hazard than traditional deductibles, *Journal of Health Economics*, vol. 28, pp. 198-209.

van Ophem, H., 1999, A general method to estimate correlated discrete variables, *Econometric Theory*, vol. 15, pp. 228-237.

van Ophem, H., 2000, Modeling selectivity in count data models, *Journal of Business & Economic Statistics*, vol. 18, pp. 503-511.

van Ophem, H., 2009, The frequency of visiting a doctor: is the decision to go independent of the frequency?, working paper, University of Amsterdam.

Winkelmann, R., 2004, Health care reform and the number of doctor visits - an econometric analysis, *Journal of Applied Econometrics*, vol. 19, pp. 455-472.

Zimmer, D.M., and P.K. Trivedi, 2006, Using trivariate copulas to model sample selection and treatment effects: application to family health care demand, *Journal of Business & Economics Statistics*, vol. 24, pp. 63-76.

Appendix: Copula's

The copula-technique was first introduced in econometrics by Lee (1983), although he did not use the term 'copula'. The idea originates from Sklar (1959). The copula approach is a useful method for deriving joint distributions given the marginal distributions, especially when the random variables are not normally distributed. I will concentrate here on the Gaussian or normal copula. Alternatives are discussed in e.g. Trivedi and Zimmer (2005).

Consider two random variables u and v with known marginal distributions $F_u(u)$ and $F_v(v)$. The transformed random variables $u^* = \Phi^{-1}(u)$ and $v^* = \Phi^{-1}(v)$ are standard normal distributed, where $\Phi^{-1}(.)$ is the inverse of the standard normal univariate cumulative distribution function. These transformed random variables can be related to each other by using the (standard) normal bivariate distribution. To accommodate a discrete or count random variable, use can be made of van Ophem (1999). The basic idea is to use the following identity:

$$Pr(u \le k) = \Phi(\eta_k) = \Phi(\Phi^{-1}(\sum_{j=0}^{k} Pr(u=j)))$$

$$Pr(v \le p) = \Phi(\lambda_p) = \Phi(\Phi^{-1}(\sum_{j=0}^{p} Pr(v=j)))$$

The bivariate probability (with nonzero correlation) $u \le k$ and $v \le p$ can now be written as:

$$Pr(u \le k, v \le p) = B(\eta_k, \lambda_p; \rho)$$

where B(.,.;.) denotes the bivariate normal cumulative distribution with mean (0,0), variance (1,1) and correlation ρ. η_k and λ_p depend on the parameters of the original marginal distributions. Maximization of the likelihood function is done across the original parameters and ρ.

Using the Gaussian copula has the advantage that ρ can take any value between -1 and 1. Computer routines to calculate the inverse of the standard normal cumulative distribution and the bivariate normal distribution are readily available in many software packages and usually yield high precision results.

Extension of the technique to higher dimensions is straightforward. See, Zimmer and Trivedi (2006) for an application for the trivariate case.

Table 1: Premium quotes of ten insurance companies (most basic package)

Insurance company	No voluntary deductible	Voluntary deductible € 500	Difference in premium
Aegon	€95.06	€80.06	€15.00
Delta Lloyd	€95.83	€79.16	€16.67
FBTO	€84.35	€63.52	€20.83
Fortis	€94.00	€83.16	€10.84
Interpolis	€94.25	€73.42	€20.83
Menzis	€92.00	€77.00	€15.00
OHRA	€94.16	€77.49	€16.67
Unive	€77.77	€56.78	€20.99
VGZ	€92.95	€77.95	€15.00
Zilveren Kruis	€92.75	€71.92	€20.83
Average	€91.31	€74.05	€17.27

Quotes found on the internet on September 4th, 2009. Quotes for a male of age 30, without a partner and children, living in Amsterdam. Basic packages may differ across insurance companies.

Table 2: Frequencies of the doctor visits

Count	N =1083		N = 855		Count	N =1083		N = 855	
0	258	(23.8%)	197	(23.0%)	10	13	(1.2%)	9	(1.1%)
1	257	(23.7%)	196	(22.9%)	12	4	(0.4%)	4	(0.5%)
2	212	(19.6%)	165	(19.3%)	13	1	(0.1%)	0	(0.0%)
3	123	(11.4%)	107	(12.5%)	15	2	(0.2%)	2	(0.2%)
4	114	(10.5%)	94	(11.0%)	16	1	(0.1%)	1	(0.1%)
5	43	(4.0%)	33	(3.9%)	25	1	(0.1%)	1	(0.1%)
6	30	(2.8%)	26	(3.0%)	26	1	(0.1%)	1	(0.1%)
7	6	(0.6%)	5	(0.6%)	30	1	(0.1%)	1	(0.1%)
8	14	(1.3%)	12	(1.4%)	40	1	(0.1%)	1	(0.1%)
9	1	(0.1%)	0	(0.0%)					

Only actually observed number of doctor visits listed. N = 1083 refers to the 2007 sample (1083 observations) and N = 855 refers to the combined 2006-2007 sample (855 observations).

Table 3: Descriptive statistics of doctor visits and having a deductible or not

Explanatory variable	Mean	Standard deviation	Number of observations = 0	Number of observations > 0
Deductible - N = 1083	0.300	0.460	754 (69.6%)	329 (30.4%)
Deductible - N = 855	0.303	0.460	596 (69.7%)	259 (30.3%)
Doctor visits - N = 1083	2.240	2.820	258 (23.8%)	825 (76.2%)
Doctor visits - N = 855	2.316	2.962	197 (23.0%)	658 (77.0%)

N = 1083 refers to the 2007 sample (1083 observations) and N = 855 refers to the combined 2006-2007 sample (855 observations).

Table 4: Descriptive statistics of the explanatory variables

Sample	N = 1083		N = 855	
Variable	**Mean (St.Dev.)**	**min - max**	**Mean (St.Dev.)**	**min - max**
able to save	0.204 (0.403)	0 - 1	0.205 (0.405)	0 - 1
age (scaled)	5.339 (1.456)	2 - 9.2	5.353 (1.437)	2.3 - 9.2
age^2 (scaled)	30.620 (15.554)	4 - 84.64	30.720 (15.434)	5.29 - 84.64
BMI (body mass index)	26.180 (4.812)	15.3 - 70.9	26.290 (4.915)	15.3 - 70.9
breadwinner	0.705 (0.456)	0 - 1	0.705 (0.456)	0 - 1
child younger than 7	0.114 (0.317)	0 - 1	0.108 (0.310)	0 - 1
chronically ill	0.282 (0.450)	0 - 1	0.289 (0.454)	0 - 1
drinker	0.064 (0.244)	0 - 1	0.067 (0.250)	0 - 1
female	0.427 (0.495)	0 - 1	0.436 (0.496)	0 - 1
good health	0.762 (0.426)	0 - 1	0.761 (0.426)	0 - 1
living in urban area	0.430 (0.495)	0 - 1	0.415 (0.493)	0 - 1
number of children	0.618 (1.032)	0 - 5	0.621 (1.046)	0 - 5
partner	0.729 (0.445)	0 - 1	0.727 (0.446)	0 - 1
self-employed	0.041 (0.200)	0 - 1	0.042 (0.201)	0 - 1
smoker	0.205 (0.404)	0 - 1	0.204 (0.402)	0 - 1

Scaling on age: age/10. Scaling on age^2: (age/10)*(age/10). N = 1083 refers to the 2007 sample (1083 observations) and N = 855 refers to the combined 2006-2007 sample (855 observations).

Table 5: Estimation results of the model with a Poisson distributed number of doctor visits. Difference between the deductible and without deductible groups only a constant.

	N = 1083	N = 855
	deductible yes/no	**deductible yes/no**
constant	0.755 (0.552)	1.038 (0.627)#
age	-0.495 (0.193)*	-0.516 (0.221)*
age^2	0.046 (0.019)*	0.049 (0.021)*
able to save	0.251 (0.099)*	0.225 (0.112)*
female	-0.172 (0.115)	-0.304 (0.129)*
number of children	-0.037 (0.045)	-0.007 (0.051)
chronically ill	-0.013 (0.017)	-0.231 (0.200)
good health	0.132 (0.198)	0.154 (0.192)
BMI	-0.005 (0.012)	-0.017 (0.016)
Expected number of doctor visits in 2006		-0.103 (0.072)
	Poisson (doctor visits)	**Poisson (doctor visits)**
constant	-0.042 (0.253)	-0.259 (0.280)
deductible = 1	-0.199 (0.070)**	-0.198 (0.080)*
age	0.089 (0.018)**	0.117 (0.019)**
female	0.246 (0.054)**	0.225 (0.063)**
child younger than 7	0.299 (0.090)**	0.177 (0.107)#
number of children	-0.074 (0.029)*	-0.067 (0.033)*
chronically ill	0.410 (0.047)**	0.434 (0.053)**
good health	-0.459 (0.048)**	-0.373 (0.055)**
BMI	0.023 (0.003)**	0.029 (0.003)**
drinker	0.029 (0.086)	-0.016 (0.092)
smoker	-0.029 (0.051)	-0.029 (0.059)
breadwinner	0.005 (0.065)	-0.024 (0.071)
living in urban area	-0.100 (0.043)*	-0.079 (0.050)
partner	-0.068 (0.056)	-0.114 (0.061)#
self-employed	-0.209 (0.123)#	-0.212 (0.139)
	Other model parameters	**Other model parameters**
γ	-0.012 (0.072)	-0.999 (0.827)
ρ	0.016 (0.049)	0.023 (0.056)
loglikelihood value	-2837.066	-2251.753

Absolute asymptotic standard errors between parentheses. **/*/# significant at 1%/5%/10% (two-sided test).

Table 6: Estimation results of the model with a Poisson distributed number of doctor visits. Difference between the deductible and without deductible groups: all parameters.

	N = 1083		N = 855	
	deductible yes/no		**deductible yes/no**	
constant	0.775 (0.539)		1.069 (0.636)#	
age	-0.492 (0.193)*		-0.550 (0.219)*	
age^2	0.046 (0.018)*		0.056 (0.021)**	
able to save	0.244 (0.099)*		0.219 (0.113)*	
female	-0.170 (0.085)*		-0.198 (0.110)#	
number of children	-0.033 (0.045)		-0.011 (0.051)	
chronically ill	-0.014 (0.102)		-0.067 (0.130)	
good health	0.157 -0,126		0.028 (0.143)	
BMI	-0.007 (0.010)		-0.007 (0.012)	
Expected number of doctor visits in 2006			-0.071 (0.070)	
	Poisson (doctor visits)		**Poisson (doctor visits)**	
	deductible = 0	**deductible = 1**	**deductible = 0**	**deductible = 1**
constant	0.391 (0.291)	-1.010 (0.514)*	-0.029 (0.331)	-0.686 (0.576)
age	0.052 (0.021)*	0.175 (0.033)**	0.090 (0.023)**	0.175 (0.037)**
female	0.183 (0.063)**	0.449 (0.117)**	0.142 (0.071)*	0.449 (0.128)**
child younger than 7	0.191 (0.100)#	0.290 (0.177)#	0.146 (0.132)	0.198 (0.204)
number of children	-0.029 (0.031)	-0.028 (0.058)	-0.062 (0.043)	-0.040 (0.065)
chronically ill	0.431 (0.055)**	0.340 (0.089)**	0.465 (0.064)**	0.282 (0.099)**
good health	-0.514 (0.055)**	-0.290 (0.096)**	-0.398 (0.063)**	-0.264 (0.105)*
BMI	0.026 (0.004)**	0.007 (0.008)	0.035 (0.004)**	0.006 (0.009)
drinker	0.122 (0.091)	-0.753 (0.277)**	0.097 (0.100)	-0.921 (0.335)**
smoker	0.035 (0.060)	-0.125 (0.113)	0.023 (0.071)	-0.116 (0.132)
breadwinner	-0.095 (0.072)	0.243 (0.136)#	-0.076 (0.083)	0.136 (0.151)
living in urban area	-0.018 (0.050)	-0.251 (0.084)**	-0.047 (0.059)	-0.269 (0.093)**
partner	-0.142 (0.066)*	0.116 (0.110)	-0.195 (0.072)**	0.081 (0.123)
self-employed	-0.241 (0.137)#	0.000 (0.259)	-0.160 (0154)	-0.142 (0.335)
	Other model parameters		**Other model parameters**	
γ	-0.024 (0.070)		-0.050 (0.072)	
ρ (deductible = 0)	0.087 (0.060)		0.083 (0.075)	
ρ (deductible = 1)	-0.132 (0.087)		-0.123 (0.094)	
loglikelihood value	-2806.252		-2222.435	

Absolute asymptotic standard errors between parentheses. **/*/# = significant at 1%/5%/10% (two-sided test).

Table 7: Estimation results of the model with a NegBin 2 distributed number of doctor visits. Difference between the deductible and without deductible groups: all parameters.

	N = 1083		**N = 855**	
	deductible yes/no		**deductible yes/no**	
constant	0.432 (0.458)		0.808 (0.597)	
age	-0.350 (0.160)*		-0.469 (0.198)*	
age^2	0.033 (0.015)*		0.050 (0.018)**	
able to save	0.184 (0.080)*		0.173 (0.097)#	
female	-0.091 (0.085)		-0.147 (0.103)	
number of children	-0.062 (0.038)		-0.043 (0.047)	
chronically ill	-0.042 (0.109)		-0.078 (0.135)	
good health	-0.026 (0.127)		-0.061 (0.135)	
BMI	0.002 (0.011)		0.000 (0.013)	
Expected number of doctor visits in 2006			-0.094 (0.067)	
	NegBin 2 (doctor visits)		**NegBin 2 (doctor visits)**	
	deductible = 0	**deductible = 1**	**deductible = 0**	**deductible = 1**
constant	-0.628 (0.463)	-0.991 (0.867)	-0.918 (0.513)#	-0.218 (1.041)
age	0.082 (0.032)*	0.215 (0.056)**	0.099 (0.035)**	0.221 (0.061)**
female	0.377 (0.106)**	0.164 (0.176)	0.360 (0.114)**	0.154 (0.188)
child younger than 7	0.187 (0.145)	0.351 (0.279)	0.010 (0.163)	0.245 (0.314)
number of children	-0.035 (0.047)	-0.072 (0.089)	-0.029 (0.049)	-0.078 (0.097)
chronically ill	0.451 (0.089)**	0.243 (0.160)	0.516 (0.099)**	0.171 (0.181)
good health	-0.602 (0.092)**	-0.477 (0.174)**	-0.483 (0.101)**	-0.498 (0.184)**
BMI	0.032 (0.008)**	0.001 (0.016)	0.043 (0.008)**	0.003 (0.016)
drinker	0.182 (0.175)	-1.092 (0.370)**	0.064 (0.163)	-1.240 (0.432)**
smoker	-0.038 (0.095)	-0.228 (0.185)	0.012 (0.999)	-0.223 (0.211)
breadwinner	0.032 (0.119)	-0.105 (0.206)	-0.019 (0.124)	-0.283 (0.220)
living in urban area	-0.049 (0.078)	-0.253 (0.142)#	-0.034 (0.081)	-0.326 (0.150)*
partner	-0.046 (0.107)	0.110 (0.190)	-0.098 (0.110)	0.052 (0.202)
self-employed	-0.169 (0.198)	-0.166 (0.370)	-0.108 (0.207)	-0.314 (0.476)

Table 7 continued

	Other model parameters	Other model parameters
γ	0.106 (0.101)	0.030 (0.070)
θ (deductible = 0)	0.752 (0.160)**	1.728 (0.187)**
θ (deductible = 1)	1.728 (0.547)**	1.112 (0.634)#
ρ (deductible = 0)	-0.799 (0.078)**	-0.755 (0.094)**
ρ (deductible = 1)	0.693 (0.193)**	0.450 (0.322)
loglikelihood value	-2659.346	-2102.582

Absolute asymptotic standard errors between parentheses. **/*/# significant at 1%/5%/10% (two-sided test).

Table 8: Estimation results of the Poisson model with semiparametric unobserved heterogeneity. Difference between the deductible and without deductible groups: all parameters.

	N = 1083		N = 855	
	deductible yes/no		deductible yes/no	
constant	0.926 (1.280)		0.994 (0.640)	
age	-0.461 (0.302)		-0.543 (0.226)*	
age^2	0.041 (0.039)		0.055 (0.021)*	
able to save	0.263 (0.098)**		0.215 (0.115)#	
female	-0.150 (0.155)		-0.224 (0.117)#	
number of children	-0.056 (0.181)		-0.022 (0.052)	
chronically ill	-0.007 (0.114)		-0.063 (0.126)	
good health	0.003 (0.928)		-0.016 (0.163)	
BMI	-0.004 (0.015)		-0.002 (0.013)	
Expected number of doctor visits in 2006			-0.065 (0.077)	
	Poisson SP (doctor visits)		Poisson SP (doctor visits)	
	deductible = 0	deductible = 1	deductible = 0	deductible = 1
constant	-0.567 (0.586)	-1.873 (0.955)*	-0.903 (0.412)*	-1.778 (0.953)#
age	0.088 (0.061)	0.197 (0.108)#	0.139 (0.029)**	0.223 (0.061)**
female	0.316 (0.116)**	0.392 (0.132)**	0.340 (0.091)**	0.522 (0.172)**
child younger than 7	0.256 (0.137)#	0.265 (0.278)	0.057 (0.154)	0.232 (0.278)
number of children	-0.079 (0.063)	0.001 (0.099)	-0.029 (0.040)	-0.021 (0.087)
chronically ill	0.321 (0.094)**	0.434 (0.195)*	0.325 (0.085)**	0.316 (0.148)*
good health	-0.512 (0.084)**	-0.324 (0.138)*	-0.437 (0.073)**	-0.208 (0.156)
BMI	0.016 (0.010)	0.012 (0.024)	0.034 (0.006)**	0.013 (0.012)
drinker	-0.003 (0.160)	-0.869 (0.341)*	-0.017 (0.117)	-1.024 (0.396)**
smoker	-0.030 (0.084)	-0.132 (0.166)	0.105 (0.077)	-0.137 (0.188)
breadwinner	0.095 (0.090)	0.153 (0.160)	0.076 (0.099)	0.1`50 (0.202)
living in urban area	-0.077 (0.087)	-0.159 (0.315)	-0.076 (0.068)	-0.245 (0.146)#
partner	-0.036 (0.189)	0.136 (0.266)	-0.041 (0.085)	0.045 (0.173)
self-employed	-0.082 (0.167)	-0.107 (0.425)	-0.040 (0.195)	-0.217 (0.427)

Table 8 continued

	Other model parameters	Other model parameters
γ	0.109 (0.806)	-0.003 (0.104)
ρ (deductible = 0)	0.414 (0.870)	0.020 (0.328)
ρ (deductible = 1)	0.024 (0.260)	-0.045 (0.347)
η_{01}	0.767 (0.240)**	1.528 (0.117)**
η_{02}	2.134 (0.254)**	-10.978 (90.31)
$Pr(\eta_{01})$	0.491 (0.160)**	0.032 (0.013)*
$Pr(\eta_{02})$	0.041 (0.069)	0.044 (0.024)#
η_{11}	1.076 (0.191)**	1.164 (0.178)**
η_{12}	2.216 (0.310)**	3.443 (0.387)**
$Pr(\eta_{11})$	0.373 (0.180)*	0.324 (0.140)*
$Pr(\eta_{12})$	0.008 (0.011)	0.005 (0.008)
loglikelihood value	-2654.641	-2082.633

Absolute asymptotic standard errors between parentheses. **/*/# significant at 1%/5%/10% (two-sided test).

Table 9: Estimated probability of having chosen for a deductible and estimated expected number of doctor visits conditional on d = 1 or d=0, based on the estimates presented in Table 8, N = 1083.

Variable change	P(deductible)	[Δ]	λ_1 |d=1	[Δ]	λ_0 |d=0	[Δ]
Reference	0.332		0.504		0.768	
age = 20	0.497	[0.165]	0.334	[-0.170]	0.560	[-0.208]
age = 30	0.397	[0.064]	0.410	[-0.093]	0.665	[-0.102]
age = 50	0.301	[-0.031]	0.619	[0.115]	0.865	[0.097]
age = 60	0.300	[-0.032]	0.761	[0.257]	0.953	[0.185]
age = 70	0.330	[-0.003]	0.936	[0.432]	1.029	[0.260]
able to save	0.432	[0.100]	0.502	[-0.002]	0.713	[-0.054]
female	0.272	[-0.060]	1.761	[0.257]	1.136	[0.368]
chronically ill	0.288	[-0.044]	1.120	[0.616]	2.023	[1.255]
no good health	0.305	[-0.027]	0.708	[0.204]	1.384	[0.615]
BMI = 20	0.342	[0.010]	0.473	[-0.031]	0.699	[-0.068]
BMI = 30	0.322	[-0.010]	0.537	[0.033]	0.844	[0.076]
BMI = 40	0.301	[-0.031]	0.610	[0.106]	1.022	[0.254]
drinker	0.317	[-0.015]	0.207	[-0.297]	0.774	[0.006]
smoker	0.330	[-0.002]	0.440	[-0.064]	0.745	[-0.023]
2 kids, age > 6	0.300	[-0.032]	0.505	[0.001]	0.664	[-0.104]
2 kids, age ≤ 6	0.295	[-0.037]	0.666	[0.162]	0.880	[0.112]
no partner	0.331	[-0.001]	0.438	[-0.066]	0.740	[-0029]
breadwinner	0.331	[-0.001]	0.591	[0.087]]	0.852	[0.084]
living urban area	0.332	[-0.000]	0.428	[-0.076]	0.707	[-0.061]
self-employed	0.334	[0.001]	0.451	[-0.052]	0.702	[-0.066]

The reference individual is a male with a partner and no children, of age 40 and in good health, not being able to save, not chronically ill, having a BMI equal to 25, not drinking or smoking, not a breadwinner, not living in an urban area and not being self-employed.