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A Comparison of Alternative Methods to Model Endogeneity in Count Models. An Application to the Demand for Health Care and Health Insurance Choice.

Martin Schellhorn

SEDAP Research Paper No. 40

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A comparison of alternative methods to model endogeneity in count models. An application to the demand for health care and health insurance choice.

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Abstract: *Several estimators have been suggested to tackle the problem of endogenous regressors and selectivity in count regression models. They differ in the structure and the degree of parametrization of the underlying models. The estimation of health services utilization conditional on the choice of different forms of health insurance provides a classical example of such problems. In Switzerland, basic health insurance is mandatory and each individual is insured separately. The insurance premium varies by region of residence but is independent of income and risk. The insured face a minimal annual deductible for ambulatory health services. Annually, they are given a choice of higher deductibles to reduce their insurance premium by a regulated percentage. The choice of a higher deductible sets incentives for a more cautious utilization of health services. Clearly, the choice is made based on expected health service utilization. The effect of the choice of a higher than the minimal deductible on the number of physician visits is analyzed. A matching estimator, a GMM estimator, two-stage method of moments estimators which account for selectivity and endogenous switching count regression models are applied to data from the 1997 Swiss Health Survey. Incentive-induced behavioral changes are disentangled from selection effects. The main finding is that most of the observed lower utilization for individuals with a high insurance deductible is caused by self-selection of individuals into the respective insurance contracts which either differ in their preferences or are healthier in unobserved aspects of their health status.*

Key words: demand for health care and insurance, count models, endogenous regressors

1. Introduction

Methods to deal with endogenous regressors and selectivity problems have been applied in linear models for a long time. They include a range of method of moments estimators, selection-correction estimators (SCE) and the estimation of simultaneous equations. Only recently, methods have been developed which deal with these problems in the context of count regressions. This paper applies several of these methods to estimate the effect of the choice of different health insurance deductibles on the demand for physician visits in Switzerland. In Switzerland, basic health insurance is mandatory and each individual is insured separately. The insurance premium varies by region of residence but is independent of income and risk. The insured face a minimal annual deductible for ambulatory health services. Annually, they are given a choice of higher deductibles to reduce their insurance premium by a regulated percentage. The choice of a higher deductible sets incentives for a more cautious utilization of health services. Clearly, the choice of deductible is made based on expected health service utilization and (at least) partially unobservable health status and risk preferences. The effect of the choice of a higher than the minimal deductible on the number of physician visits is analyzed. This is a classic example of an endogenous regressor and selectivity problems in count regression. The coefficients in the estimation of health care utilization conditional on the choice of a specific health insurance contract can be biased if the potential endogeneity of this regressor is ignored. An estimate of the effect of the choice of a specific contract would mix up selection effects and a behavioral effect induced by the incentives of the contract.

A GMM estimator, two-stage method of moment estimators which control for selectivity, switching regression estimators (SRE) and a matching estimator are applied to disentangle selection effects from induced behavioral changes. They assume different structures and parametrization for the underlying model of the effect of the choice of the health insurance deductible on the demand for physician services. All estimators have in common, that the choice decision is explicitly modeled by a binary choice model, e.g. a probit or a logit model. Except for the SRE approaches all estimators assume that the choice of a high health insurance deductible alters the number of physician visits by a certain percentage. The matching estimator refrains from modeling the functional form of the utilization equation. Only an estimate of the induced reduction in physician visits caused by the choice of a high deductible is obtained. The GMM estimator only models the conditional mean of the number of physician visits. Hence, coefficients for all covariates in the utilization equation are obtained. The structure of the underlying model is comparable in the SCE approaches. In contrast to the GMM estimator, an estimate for the correlation between the error terms in the choice and utilization equations is obtained. Also, a more parametric version of this two-stage method of moments estimator explicitly assumes that physician visits follow a Poisson distribution. Finally, the SRE approach allows the coefficients of all covariates in the utilization equation to vary with the choice of the deductible. The (potentially) induced reduction in the number of physician visits depends on all other covariates.

Several studies have analyzed the impact of varying insurance contracts on health care utilization behavior. The amount of the actual reduction in medical services utilization has been analyzed by Newhouse et al. [1] for various levels of co-payments. They used data from a randomized experiment, the RAND study. The first study that analyzed the choice of insurance status and health care utilization simultaneously was Cameron et al. [2]. They find that health status appears to be more important in determining health service utilization than health insurance choice, while income seems to be more important in determining health insurance choice than health care service use. Also, they find evidence that both, moral hazard and self-selection of individuals into different insurance contracts are important determinants of health care utilization. In an analysis of Swiss data from 1992, Holly et al. [3] simultaneously model admission to a hospital and the availability of supplementary insurance coverage. They find a significant positive impact for the availability of supplementary insurance on hospital admissions.

Potentially, all health status variables could be endogenous regressors, too. I refrain from modeling health status variables as endogenous as I use long-term morbidity indicators only which should not be influenced by health care utilization.

The paper proceeds as follows. In the second section the different estimators are presented. This is followed by a section which describes the Swiss Health system and the data set which is used in this study. Section four gives results and the paper finishes with concluding remarks.

2. Econometric Models

2.1 Model specification

In modeling the demand for physician visits one has to take into account that physician visits are a count number. Various econometric models for count data (see e.g. Cameron and Trivedi [4]) have been applied in a number of studies on the demand for health care. Most of these models give consistent estimates only when the regressors are exogenous. In the present study, however, the main regressor of interest is the chosen deductible, which is likely to be endogenous. The general model for the number of physician visits of individual i, y_i, is specified in the following way:

$$
\begin{aligned}
& y_i \sim F(x_i, d_i, b_d, e_i) \\
& d_i = \begin{cases} 1 & iff \quad z_i\,'a + v_i > 0, \\ 0 & otherwise \end{cases} \\
& Cov(e, v) = \Sigma_d = \begin{bmatrix} s^2 & s\,r \\ s\,r & 1 \end{bmatrix},
\end{aligned}
\tag{1}
$$

where x_i are the exogenous covariates, d_i is a dummy-variable indicating the choice of a high deductible, b_d are unknown coefficients of a count distribution *F(.)* and e_i is an error term. The equation for the choice of the deductible can be estimated by standard probit or logit approaches with z_i being covariates, a the coefficients and n_i an error term. For simplicity of notation, the individual subscript is dropped in the following.

Both the GMM estimator and the two-stage method of moments estimators assume that the choice of a high deductible has no impact on the coefficients in the equation for the number of physician visits, i.e. $b_0 = b_1 = b$. The chosen deductible enters the regression in the form of a dummy variable. The number of physician visits y and the choice of the deductible d are modeled with a simultaneous equation approach. The number of physician visits y depends on the chosen deductible d and covariates x. The choice of the deductible d depends on covariates z which potentially include the number of physician visits.

$$y = \exp(d\,d + x'b) * e,$$

(2) $$d = \begin{cases} 1 & iff \quad g\,y + z'a + n > 0, \\ 0 & otherwise \end{cases}$$

$$Cov(e, v) = \Sigma_d = \begin{bmatrix} s^2 & s\,r \\ s\,r & 1 \end{bmatrix},$$

There is no simple equation for the reduced form for *d*.

As the probabilities for the possible realizations of *d* have to add up to one it is easily established that the model is only logically consistent if either $d = 0$ or $g = 0$ as

(3) $$\Pr(d = 1) + \Pr(d = 0) = \Phi(g \exp(d + x'b) + z'a) + (1 - \Phi(g \exp(x'b) + z'a)$$

It follows that if a binary variable is entered in the exponential mean function of the count variable, and the two variables are simultaneously determined, this simultaneity only arises via the correlation of v and e.

The deductible is chosen at the beginning of the year (conditional on the distribution of the expected number of physician visits), while the physician visits occur after this choice is made. Taking this fact into consideration $g = 0$ seems a natural choice for the specification of the model.

2.2. The GMM estimator

The first attempt to solve the problem applies a generalized method of moments (GMM) estimator developed by Windmeijer and Santos-Silva [5] and Mullahy [6] for count data with endogenous regressors.

The conditional mean of the count variable is specified as

(4) $$E(y \mid x) = m = \exp(x'b),$$

The conditional mean of y implicitly defines a regression model

(5) $$y = \exp(x'b + t) = \exp(x'b) * e = me$$

If some of the k elements of x are endogenous the Poisson estimator will be inconsistent because $E(e \mid x) \neq 1$. GMM techniques are applicable if instruments z are available such that $E(e \mid z) = 1$. The GMM estimator is based on the residual v-1, which is equal to (y-m)/m. Windmeijer and Santos-Silva derive a two-step GMM estimator and give optimal instruments. The estimator minimizes the objective function

(6) $$(\tilde{y} - \tilde{m})' M^{-1} Z (Z' \tilde{\Omega}^* Z)^{-1} Z' M^{-1} (\tilde{y} - \tilde{m})$$

where $\tilde{y}, \tilde{m}$ are column vectors of the observations and conditional means, $M = diag(\tilde{m})$, Z is an $N \times g$ matrix of instruments, and $Z'\Omega^* Z$ is the asymptotic variance of $Z' M^{-1} (\tilde{y} - \tilde{m})$. The optimal instruments are given by $Z^* = E(\Omega^{*-1} WX \mid Z)$, with $W = \mathrm{diag}(\tilde{y} / \tilde{m})$. In the case of no endogenous regressors, $\mathrm{Z} = \mathrm{X}$, and with $\Omega^* = M^{-1}$, the objective function of the multiplicative Poisson model becomes

(7) $$(y - m)' M^{-1} X (X M^{-1} X)^{-1} X M^{-1} (y - m) .$$

This is equivalent to a heteroscedasticity corrected objective function which allows for overdispersion and its minimization will not yield Poisson ML results. The GMM estimator can be applied when there is more than one endogenous regressor. It also accommodates endogenous regressors which are not binary. In Schellhorn [7] the choice of the deductible is estimated by an ordered logit model.

2.3. Selection-correction estimators

Mullahy [6] and Terza [8] define a model with an additive and a multiplicative error term

(8) $$y = \exp(a\, d + x' b + t\,) + h = \exp(a\, d + x' b\,) * e + h,$$

in which the multiplicative error term is correlated with the regressors but not the additive one. Windmeijer and Santos-Silva [5] note that this model is observationally equivalent to the model with only multiplicative errors.

Two-stage method of moments estimation

Terza [8] develops a two-stage method of moments estimator in the spirit of Heckman's two-stage estimator for linear models with endogenous dummies. If e were known then standard non-linear regression would be applicable. Terza derives the conditional expectation of the multiplicative error term to be

$$(9) \qquad E[e \mid v, w] = \exp\{r s n + \frac{1}{2} s^{2} (1 - s^{2})\},$$

where $w = (z, x)$. It follows that the conditional expectation of the count variable is

$$(10) \qquad E\left[y \mid v, w\right] = m\left(b^{*}\right) y\left(q, a\right) = h\left(w, d, b^{*}, q, a\right)$$

where

$$(11) \quad y\left(q, a\right) = \exp\left\{-\tfrac{1}{2} q^{2}\right\}\left(dE\left[\exp\{q v\} \mid v > -za, w\right] + (1 - d) E\left[\exp\{q v\} \mid v \leq -za, w\right]\right)$$

and

$$(12) \qquad m\left(b^{*}\right) = \exp\left\{x b^{*}\right\}$$

b^{*} is the same as b except for the constant which is shifted by $s^{2}/2$ and $q = r s$. The actual realization of y can then be written as $y = h\left(w, d, b^{*}, q, a\right) + e$. Terza notes that $y\left(q, a\right)$ is similar to the selection-correction term (inverse Mill's ratio) in Heckman's [9] linear model. Calculating the conditional expectations for $E\left[\exp\{q v\} \mid v > -za, w\right]$ and $E\left[\exp\{q v\} \mid v \leq -za, w\right]$ and plugging in the results simplifies $y\left(q, a\right)$ to

$$(13) \qquad y\left(q, a\right) = d \frac{\Phi\left(q + za\right)}{\Phi\left(za\right)} + (1 - d) \frac{1 - \Phi\left(q + za\right)}{1 - \Phi\left(za\right)}$$

where $\Phi(.)$ denotes the standard normal cumulative distribution function (cdf). It is theoretically possible but computationally burdensome to jointly obtain estimates for b^{*}, q and a by applying nonlinear least-squares to the "full" problem. Terza therefore suggests applying a two-stage technique. In the first stage consistent estimates for a are obtained by a simple probit analysis of the endogenous dummy variable. The second stage obtains estimates for b^* and q by applying nonlinear least-squares to $y = h\left(w, d, b^*, \hat{a}\right) + e^0$. Terza derives the asymptotic properties of these estimates.

Nonlinear weighted least-squares Poisson estimation

If the distribution function $f\left(y \mid w, d, e\right)$ of the count variable is specified instead of just the first conditional moment efficiency can be gained by applying full information maximum likelihood (FIML) or nonlinear weighted least squares (NWLS). As FIML is computationally burdensome Terza suggests applying NWLS. He notes that the general expression for the conditional variance of the nonlinear least squares error term is

$$\text{var}\left(e \mid w, d\right) = E\left[\text{var}\left(y \mid w, d, e\right)\right] + \text{var}\left(E\left[y \mid w, d, e\right]\right). \tag{14}$$

He then derives this expression for the case of the Poisson distribution and develops an estimator for it. In addition to performing the two-stage method of moments estimation this involves obtaining a consistent estimate of s^2.

The estimated conditional variance is used as weight in the following NWLS estimator.

$$\tilde{b} = \begin{bmatrix} \tilde{b}^* \\ \tilde{q} \end{bmatrix} = \arg\min Q^*\left(b^*, q\right) \tag{15}$$

where

$$\begin{gathered} Q^*\left(b^*, q\right) = \sum_{i=1}^{n} e_i^{*2} \\ e_i^{*2} = \frac{y_i - h\left(w_i, d_i, q, \hat{a}\right)}{\sqrt{\hat{v}_i}}; \quad \textit{and} \quad \hat{v}_i = \hat{\text{var}}\left(e_i^* \mid w_i, d_i\right) \end{gathered} \tag{16}$$

Again, Terza derives the asymptotic properties of this estimator. An estimate for the correlation r is finally defined by

(17) $$\hat{r} = \frac{\hat{q}}{\sqrt{\hat{s}^2}}.$$

2.4. Endogenous switching count regression models

Finally, a maximum likelihood estimator will be applied which allows the coefficients in the equation for physician visits to vary with the choice of the deductible. It is developed in detail in van Ophem [10]. This SRE approach allows the effect of the choice of a higher deductible to depend on all other characteristics. However, the effect is more difficult to interpret as it is not given by a single coefficient. This approach seems appropriate, when there is reason to believe, that the choice of a higher deductible affects individuals with different socio-economic characteristics differently.

(18) $$\begin{aligned} & y = \exp(x' b_d + e_d), \\ & d = \begin{cases} 1 & iff \quad za + v > 0, \\ 0 & otherwise \end{cases} \\ & Cov(e_d, v) = \Sigma_d = \begin{bmatrix} s^2 & sr \\ sr & 1 \end{bmatrix}, \end{aligned}$$

The probability that the number of physician visits of individual i is less than or equal to a number k can be written as $\Pr(y \le k \mid x, d) = P_d(k; b_d \mid x)$. It is assumed that the probability that the count takes on any nonnegative number is strictly positive. If b_d takes on a particular value and x is given, then there exist unique values $h_{0,d}, h_{1,d}, h_{2,d}, \ldots$ such that:

(19) $$\Pr(y \le k \mid x, d) = \sum_{k=0}^{k} P_d(k; q_d \mid x) = \Phi(h_{k,d} \mid x) = \int_{-\infty}^{h_{k,d}} f(u \mid x) du$$

where $\Phi(.\,|\,x)$ and $f(.\,|\,x)$ denote the cumulative distribution function (cdf) and probability density function (pdf) of the standard normal distribution. As the probability for any nonnegative value is assumed to be positive it is easily established that the $h_{k,d}$ are strictly increasing in k. From (19) we get:

$$h_{k,d} = \Phi^{-1}\left(\sum_{k=0}^{k} P_d(k; q_d \mid x)\right) \tag{20}$$

By this transformation, an arbitrary count distribution can be related to the normal distribution. A similar transformation can be applied to the error term of the selection equation. Let $F_n(n; a \mid z)$ denote the cdf of the error term in the selection equation. Then, $v^* = \Phi^{-1}(F_v(v \mid z))$ has a standard normal distribution. Following Maddala [11], a cumulative bivariate distribution with marginal distribution $F_j(e_j)$ and correlation r_e between e_1 and e_2 is given by:

$$H(e_1, e_2; r_e) = B(u_1, u_2; r_u) = B(\Phi^{-1}(F_1(e_1)), \Phi^{-1}(F_2(e_2)); r_u)\,, \tag{21}$$

where *B( )* is the cumulative bivariate normal distribution with zero means, unit variances and correlation r_u. In the present case, there is a combination of a discrete and a continuous random variable, which both have been transformed to the normal distribution. Of the continuous random variable it is only known whether it is above or below some value. Consequently, the probability of the count not exceeding k and observation i falling in regime 0 can be written as:

$$\Pr(y \le k, d = 0) = \Pr(y \le k, v < -z'a) = B(h_{k,0}, \Phi^{-1}(F_v(-z'a)); r_u) \tag{22}$$

From this, the likelihood of each observation can be derived and the likelihood function is generated by multiplying across all observations.

To obtain conversion of the maximum likelihood algorithm, the observed number of physician visits had to be top-coded at $k = \bar{k}$. The necessary adjustments to the model are straightforward. The likelihood of a top-coded observation in regime 0 turns out to be:

$$\Pr(y \ge \bar{k}, d = 0) = 1 - \Pr(y \le \bar{k} - 1, d = 0) = 1 - B(h_{\bar{k}-1,0}, \Phi^{-1}(F_v(-z'a); r_u) \tag{23}$$

The estimator is very flexible with respect to the distributions assumed for the count and the error in the selection equation. In the application I use the Poisson distribution and a Without-Zero model, suggested by Mullahy [12]. This model accounts for overdispersion resulting from an excess number of zero observations. The probability of a non-zero outcome is reduced by an amount j_d and the probabilities of the resulting model equal

$$
\begin{aligned}
&P(y_d = 0) = j_d + (1 - j_d)\exp(-m_d); \quad d = 0,1; \\
&P(y_d = k) = (1 - j_d)\frac{\exp(-m_d)m_d^{\;k}}{k\,!}; \quad d = 0,1; k = 1,2,3,...
\end{aligned}
\tag{24}
$$

The Poisson model results as a special case of the Without-Zero-model if $j_d = 0$.

The estimator can be extended to accommodate multivariate endogenous selection, but will for larger dimensions require simulation estimation techniques and become computationally burdensome.

2.5. A matching estimator

Rosenbaum and Rubin [13] developed this estimator which has become very popular in the estimation of causal effects of labor market programs recently.

Let y_1 be the number of physician visits if an individual chooses a high deductible and y_0 if she does not. The goal is to estimate the expected difference $E(y_1 - y_0)$. If individuals were randomly selected into the insurance contracts with different deductibles the effect could be estimated by simply comparing the average number of visits of individuals with and without a high deductible. This setup was used in the RAND experiment to analyze the effect of different co-payment rates in health insurance (see Newhouse [1]). However, with survey data at hand one has to take into account that individuals may self-select themselves into different insurance contracts. If one could observe the number of physician visits for the same individuals with different insurance contracts the effect of the choice of a high deductible could again be estimated by comparing the average number of visits of the "treatment" group with a high deductible to the number of visits in the "control" group with a low deductible. As individuals can only choose a high or a low deductible the counterfactual is never observed. The idea of the matching estimator is to construct the counterfactual. An artificial control group is built by finding “close” matches for individuals who chose a high deductible out of the group of individuals who chose a low deductible. Theoretically, one could try to match individuals on all individual characteristics x. However, this gets problematic as the number of characteristics grows large. Rosenbaum and Rubin establish that if such a matching on x is valid, then - under certain conditions - matching on the propensity score $P(x) = P(d = 1 | x)$ is valid, too. The necessary conditions are the following

(25) $$(y_0, y_1) \perp d \,|\, x \Leftrightarrow P(d = 1 | y_0, y_1, x) = P(d = 1 | x) \quad \text{and}$$

$$0 < P(x) < 1$$

The first condition is also used in the count regression models for consistency reasons. It is a non-causality condition that excludes the dependence between the potential outcomes and the choice variable d. The second condition guarantees that matches can be made for all values of x. The slightly stronger restriction of a common support is applied in this study. This means that observations are deleted if their choice probability lies outside of the support of the matching group. Usually, this implies that the result of the matching estimator can only be interpreted as reflecting the effect of the “treatment on the treated”. However, no individuals of the high deductible group had to be excluded. If both conditions are satisfied then matching on the propensity score P(x) balances the distribution of y_1 and y_0 with respect to d. The validity of this approach relies critically on these conditions, see e.g. Heckman et al. [14].

This estimator refrains from specifying the functional form for the number of physician visits. No information is obtained on the impact of the covariates on the utilization of medical services. Lechner and Gerfin [15] extend the matching approach to estimate the effects of more than one mutually exclusive treatment on an outcome. Using this approach allows, for example, estimating the effect of different health plans on health service utilization.

3. An Application to the demand for physician services and the choice of health insurance in Switzerland

3.1. The Swiss health system

Switzerland has experienced a major health system reform in 1996. In Switzerland and in many other countries cost in the health care sector are continually rising. The introduction of consumer incentives in health insurance contracts was suggested in many health system reform proposals (see e.g. Leu [16] for Switzerland). These incentives are expected to reduce overutilization of medical services by partially removing distortions to consumers' health service prices. To reduce moral hazard the mandatory basic health insurance contract has a minimal annual deductible and co-payments for ambulatory services. This basic health insurance is provided by competing private insurers and covers a widely defined set of medical services. The health insurance premium is heavily regulated. Premiums for adults can vary between three regions in each canton but are not allowed to be related to risk-factors like age and sex or income. Every individual is insured with a separate contract. A choice of higher deductibles and lower premiums is offered, setting incentives for more cautious utilization. The insured have free choice between the insurance companies with open enrollment and can change their insurer and their deductible at the beginning of each calendar year. In 1997, the average monthly insurance premium for the contract with the minimal deductible varied between 130 SFr. per person in the canton of Appenzell and 300 SFr. in the canton of Geneva. There is a co-payment rate of 10% for ambulatory services when costs exceed the chosen deductible. There is a ceiling for co-payments of 600 SFr. per year irrespective of the chosen deductible. Health insurance premiums and out-of-pocket payments can eat up a substantial part of household income especially in larger families. Maximal premium reductions for higher deductibles are regulated. In 1997, the insured faced a choice between a minimal deductible of 150 SFr. and higher deductibles of 300, 600, 1200 or 1500 SFr. Premium reductions were regulated to be at most 8%, 15%, 30% and 40% of the premium with the minimal deductible. Therefore, the potential savings from choosing a higher deductible vary substantially between cantons and regions.

3.2. The data

The data stem from the Swiss Health Survey 1997. It was collected by the Federal Bureau of Statistics (BFS). Information was collected from 13004 individuals aged 15 and older by telephone interviews. 10000 of them also replied to a written questionnaire. The number of observations had to be reduced to 9003. Firstly, because of missing information on income and other socio-economic variables and secondly, because all individuals who were still in education had to be eliminated because special insurance premiums apply for them. In this paper I only give estimates for the effect of the choice of a higher deductible for men. Separate estimation by gender is warranted by the fact that all pregnancy related health care cost and several preventive medical examinations for women are exempt from the deductible and might alter the behavior. Results for women with the GMM approach can be found in Schellhorn [4]. Results for the other approaches are available by the author upon request. The sample used in the estimations consists of 4057 men.

Table 1 gives descriptive statistics for all remaining men, for the subgroups with low and high deductible and for the matching group. Foreigner is a dummy variable which indicates that the individual does not have a Swiss citizenship. The variable French/Italian denotes the language used in the interview (the reference category is German). Four areas of residence are differentiated by dummy-variables. Metropolitan area defines the area of residence to be in or around one of the five biggest cities in Switzerland (Basle, Bern, Geneva, Lausanne and Zurich), larger towns are the 20 towns next in size and their surroundings, small towns and their surroundings form the next category and the periphery/countryside is the reference category. The socio-professional categories were defined by the position actually held or if this was not possible by the last professional position. The omitted reference category is blue collar workers. For labor market status the omitted category is full-time working. A dummy variable indicating the existence of a chronic condition and long-term self-assessed health (SAH) are used as morbidity indicators. This long-term SAH variable was constructed from two questions. The first was a question on how the individuals rated their health at the moment, with five possible answers (very good, good, average, poor, very poor). The second question asked the individuals to compare their momentary health status with their long term health status (better, equal or worse than usually). The long-term SAH was constructed by correcting the momentary SAH by one category if the second question was answered with “better” or “worse”. There were relatively few individuals who rated their long-term

SAH as poor or very poor. As the results for these two categories did not differ much form the results for average SAH these three were grouped together and used as reference category. Further health related variables are under- and overweight. These are defined as the body mass index being below 20 or above 30, respectively. Income is equivalized monthly household income. The variables urban canton, Geneva/Vaud, roman canton and rural canton (reference category) group the cantons into four regions with similar insurance premiums and mother language. Urban cantons are the six cantons Zurich, Bern, Basel-Stadt, Basel-Land, Solothurn and Fribourg. All but the last one are in German speaking Switzerland, the last one is bilingual. The premiums in the most expensive regions of these cantons varied between 233 SFr. and 183 SFr. whereas the premiums in the cheapest regions varied between 169 SFr. and 185 SFr. The cantons Geneva and Vaud had the highest average premium with 298 SFr. in Geneva (only one region) and 258 SFr. in the cheapest region of Vaud. The roman cantons are formed by the Italian speaking Ticino, and the French speaking cantons Neuchatel, Jura and Valais. Premiums varied between 180 SFr. and 220 SFr. there. The reference category is formed by rural German speaking cantons with low average premiums that varied between 160 SFr. and 140 SFr. per month.

Figure 1 describes the distribution of all physician, primary physician and specialist visits for men with high and low deductibles, respectively. Lower utilization of medical services is observed for individuals who choose a higher deductible. However, it is not clear how much of the reduction in utilization can be attributed to induced behavioral changes on the one hand and self-selection of healthier individuals into the respective insurance contracts on the other.

3.3. Identifying exclusion restrictions and instruments

Except for the matching estimator all other approaches require an exclusion restriction for the models to be identified. One has to find instruments that play a role in determining the choice of the deductible but can be excluded from the utilization estimation. These additional instruments include the availability of supplementary insurance cover and three dummies that categorize cantons in groups with a similar premium level. Finally, the predicted choice of the deductible derived form the estimation of the choice equation is used as an instrument in the GMM approach. Having had an accident last year is excluded from the choice equation as accidents happened after the choice was made. The remainder of the paragraph motivates the exclusion restrictions.

In Switzerland, supplementary insurance only covers additional health care cost arising from a more luxurious hospital infrastructure (one and two-bed rooms) and free choice of senior physicians with higher prices. It has consequences neither for treatment in the ambulatory sector nor for an individual's out-of-pocket payments. Therefore, it should not directly influence the number of physician visits. However, the availability of supplementary insurance cover is related to the choice of deductible. Both are influenced by income and unobservable personal risk preferences. As displayed above, insurance premiums vary considerably between cantons. Still, there are no large differences in the quality of physician services throughout Switzerland. Within cantons with similar insurance premiums the potential savings from choosing a higher deductible are comparable. Therefore, supplementary insurance cover and the dummies for regions with similar premiums should provide valid instruments for estimation. This view is supported by the fact, that the coefficients of these variables are insignificant when they are added to the utilization equation. Within each canton there are up to three regions with different premiums. These regions are to accommodate different health utilization patterns within the canton. The within canton premium differences appear mostly between urban centers and the countryside. They are at least partially caused by differences in physician and hospital-bed density. As these are important supply-side determinants of health care utilization the areas of residence cannot be used as additional instruments. Finally, the predicted choice of the deductible is orthogonal to the error term in the choice equation and therefore also orthogonal to the error term in the utilization estimation in the GMM approach.

For the GMM approach the validity of the instruments is tested by applying the standard GMM $c^2 -$ test for the overidentifying restrictions.

4. Results

4.1. The choice of the deductible

Table 2 gives the estimation results for the choice of the deductible. I only display the results of independently estimated probit models. The coefficients of the choice part in the SRE approaches were almost identical. The choice is explained by age, socio-economic factors like citizenship, mother language, area of residence, education and labor market status, long-term health status, behavioral variables like drug utilization, the log of income and the additional instruments discussed above. Results are shown for two specifications. The second omits alcohol and drug utilization behavior. It is only used in the SRE approaches to reduce computational burden. There is considerable variation in the estimated probabilities. They range from 0,003 to 0,825.

In general, the probability to take a higher deductible decreases with age. Possible explanations for this finding are that individuals might become more risk averse as they grow older and a correlation of age with unobserved morbidity. The areas of residence and labor market status are insignificant in the choice equations. The coefficients on the morbidity indicators are significant and have the expected signs. Being overweight reduces the probability of taking a higher deductible. Of the behavioral variables smoking habits significantly influence the deductible choice. On average, ex- and heavy smokers take lower deductibles as those that never smoked. Having a higher income significantly increases the probability to take higher deductibles. The same is true for the existence of supplementary insurance cover. Apparently, individuals who are willing to pay for free choice of the physician and more comfort at the hospital are also willing to take the (relatively small) risk of a higher deductible. Living in a canton with a high health insurance premium increases the probability to take a higher deductible. On the one hand, the maximum out-of-pocket payments that the insured has to face when choosing a higher deductible are identical over all cantons. On the other hand, the absolute reduction of premiums is much larger in the cantons with high premiums.

4.2. Health service utilization

The number of physician visits is specified to be conditional on age, socio-economic factors like citizenship, mother language, area of residence, education and labor market status, health, behavior like drug utilization and the choice of the deductible. The coefficient on the chosen deductible should only reflect induced utilization changes when the selectivity bias is removed by applying the GMM or SCE approaches.

Tables 3 and 4 give the estimation results for all/primary physician visits for the GMM and SCE approaches (Tables 3a and 4a) and for the SRE (Tables 3b and 4b) approaches. I refrain from displaying results for specialist visits. Primary physician and specialist visits simply add up to all physician visits and the coefficients for all physician visits are simply a weighted average of the coefficients in those utilization categories. Figure 1 also shows that the observed reduction in the number of visits is more pronounced in all physician and primary physician visits than in specialist visits. To achieve convergence in the SRE approaches the number of visits had to be artificially censored. Top-coding was imputed at ten visits for the Poisson specification for all visits (nine visits for primary visits) and at twelve visits for the Without-Zero specification. As the Without-Zero specification did not detect any significant correlation between the error terms, I also carried out Without-Zero estimations with exogenous switching. For this purpose the correlation parameters were fixed at zero and no censoring was necessary. These estimates also provide some insight on the effect of the top-coding. Most of the significant coefficients keep their sign and significance. The coefficients using non-censored observations seem to be slightly larger than the estimates from the endogenous switching approach.

In all estimations the coefficients on dummy variables indicate a percentage change in the conditional mean of utilization, while the coefficient on the logarithm of income can be interpreted as the income elasticity of utilization.

The effect of the deductible: self-selection vs. induced behavioral changes

The coefficient which should be the most affected by controlling for endogeneity is the one on the choice of the deductible. The multiplicative Poisson model which assumes exogeneity shows a significant reduction of all physician as well as of primary physician visits by around thirty percent. The GMM and the two-step NLS approach provide insignificant and slightly positive coefficients. A Hausman test for endogeneity in the GMM approach finds the change in the coefficient on the deductible significant and thereby rejects exogeneity. The GMM approach is validated as the overidentifying restrictions cannot be rejected on the five percent level. Surprisingly, the two-step Poisson estimator finds a significant increase in the number of physician visits. This completely counterintuitive finding could be caused by the fact, that imposing the Poisson distribution is forcing an inappropriate structure on the data. The SCE approaches give a negative significant value for the correlation between unobservables in the choice and utilization equation. Unobservable characteristics like unmeasured differences in health status or preferences that lead to the choice of a higher deductible in health insurance also decrease the number of physician visits. The change in the coefficient on the deductible between the GMM estimator and estimations which assume exogeneity of this choice can be explained by this.

The effect of the choice of a high deductible is more difficult to judge from the SRE results as there is not a single coefficient to measure it. Following the ideas put forward by Oaxaca [17] in the literature on wage discrimination the unconditional ratio of the expected number of physician visits at the mean values of the two subgroups can be written as follows

(26)
$$\begin{aligned}\frac{E(y_0 \mid \bar{x}_0, b_0, j_0)}{E(y_1 \mid \bar{x}_1, b_1, j_1)} &= \frac{(1-j_0)\exp(\bar{x}_0' b_0)}{(1-j_1)\exp(\bar{x}_1' b_1)} = \frac{(1-j_0)}{(1-j_1)}\exp\left[(\bar{x}_0' b_0)-(\bar{x}_1' b_1)\right] \\ &= \frac{(1-j_0)}{(1-j_1)}\times\exp\left[(\bar{x}_0-\bar{x}_1)\frac{b_0+b_1}{2}\right]\times\exp\left[(b_0-b_1)\frac{\bar{x}_0+\bar{x}_1}{2}\right].\end{aligned}$$

The first term is the difference caused by a different number of zero observations in the two subgroups. The second term is the difference explained by differences in observed means and the third term is the difference caused by a different behavior in the two subgroups. This ratio is unconditional in that the predicted numbers of physician visits are calculated independently of the individuals actual choice of the deductible. Hence, the ratio is independent of selection effects. As these were found to be negligible in the without-zero specifications this does present a problem when applying this decomposition to explain the differences. With the coefficients of the without-zero specification with exogenous switching the predicted number of all physician visits at the mean of the explanatory variables of the relevant subgroups are 3,13 for the low deductible and 1,82 for the high deductible. These predicted numbers differ from the means of the subgroups because of the nonlinearity of the count model but the ratio is practically the same (1,72 at the mean values vs. 1,67 in the mean of realisations). This ratio is caused by a factor of 1,22 for the additional zero observations, only 1,05 for the difference in the means and a factor of 1,34 for the different coefficients in the count regression. This factor provides an upper bound to the incentive-induced behavioral changes. However, it is impossible to tell if it reflects only induced changes. Although no significant selection effects on unobservables were found in the without-zero specification it is possible that the different coefficients reflect differences in preferences. Additionally, some variables might not reflect the same information in the subgroups. For example, foreign citizens who live in Switzerland are a very heterogeneous group. For primary physician visits, the ratio of the predicted number of visits is 1,78 (2,02 visits for the low and 1,14 for the high deductible). This ratio is the product of a factor of 1,26 for a different number of additional zero observations, a factor of 1,16 for differences in the means of the explanatory variables and a factor of 1,21 for the difference on coefficients.

The result of the matching estimator can be derived from Table 1. The matching approach seems to work well in balancing the distributions of the treatment and matched control group. The descriptive statistics for both groups are close whereas there are big differences when comparing the statistics of the treatment group with all individuals who opted for a low deductible. The difference in the means between all physician visits of the treatment group and the matched control group is 0,988 for all physician visits with a standard error of 0,234. The respective difference for primary physician visits is 0,564 with a standard error of 0,151. This would imply that the number of all (primary) physician visits is reduced significantly by 32 percent (30 percent). This contrasts the findings of the GMM and SCE approaches which found no significant reduction in physician visits. Utilization of all (primary) physician visits was lower in the treatment group for 441 (395) matches, equal in 164 (236) and higher in 253 (227) cases. The validity of the matching estimator critically relies on the choice decision being reasonably well explained. If variables which have an important impact on the choice and utilization are unobservable, the validity of the results becomes limited. The data contains no information on the number of visits prior to the choice of the deductible which is an important determinant in the choice decision and is also correlated with current utilization. Also, health status and risk preferences are not perfectly observed.

The effect of the choice of a high deductible is more difficult to judge from the SRE results as there is not a single coefficient to measure it. It is impossible to tell if the differences in the coefficients for the exogenous regressors in the two subgroups reflect induced behavioral changes, self-selection of individuals with different preferences into the respective insurance contracts. It is also possible that some variables might not reflect the same information in the subgroups. For example, foreign citizens who live in Switzerland are a very heterogeneous group.

Determinants of utilization

The number of physician visits is increasing with age for all estimators. The effect is more pronounced for primary physician visits. The SRE approach additionally finds that it is more pronounced in the high deductible group. Off the GMM and SCE approaches only the two-step NLS estimator finds a significant positive coefficient for foreign citizens. However, the SRE approach finds opposing significant coefficients in the two regimes. While not being a Swiss citizen decreases the number of visits in the high deductible group, foreigners see their physicians more often if they chose a low deductible. As mentioned above, a possible explanation for this would be, if there were two distinctly different groups of foreign citizens in the two subgroups. Foreign citizens live in Switzerland for different reasons. They are part of the regular labor force or seek for asylum, they can be unskilled temporary workers or highly skilled long-term residents. Again, only the SRE finds a significant impact of the mother language. In the subgroup with the high deductible utilization is significantly higher. Living in a metropolitan area reduces the number of primary physician visits but has only a small impact on all visits. The reason seems to be that specialist density is higher in these areas and they seem to pick up some of the visits that primary physicians get in more rural areas. A higher educational degree leads to lower utilization of primary physician services while only a small effect is found on all visits. The SRE approaches show that this lower utilization is mainly caused by individuals with high deductibles. While relatively small effects are found for professional status in the GMM and SCE approaches the SRE finds opposing significant effects in the subgroups for primary physician visits. Having a higher position or being self-employed increases the number of visits for individuals with a high deductible and lowers it for those with a low one. All estimators find that the number of visits is lower for full-time working individuals than for part-time working, retired or unemployed individuals. As these variables might contain some health related information this result was expected. The health status variables have the expected signs and the coefficients are highly significant across all approaches. Being under- or overweight increases physician service utilization in most GMM and SCE approaches. The SRE results indicate that a Body Mass Index below 20 decreases utilization in the high deductible subgroup while the opposite is true in the low deductible subgroup. The evidence on the impact of the life-style variables alcohol, tobacco and drug consumption shows that individuals who have quit smoking see physicians more often. For the other life-style variables the evidence is inconclusive.

The GMM and SCE estimators do not find a significant income elasticity for the number of all physician visits and only Terza's two-step NLS estimator finds a negative income elasticity of 32 % for primary physician visits. This finding is not in line with other studies like Cameron et al. [2]

and Holly et al. [3] and Leu and Gerfin [18] who find that income has a significant impact on health service utilization. A significant negative income elasticity of around 15% is found in the without zero specification of the SRE approaches for the subgroup of individuals who opted for the minimal deductible.

5. Discussion

This paper applies four recently developed estimators which allow the estimation of non-linear or count data models with endogenous regressors and selection effects. The estimators differ in the structure of the underlying models as well as in their parametrization. Which estimator should be the preferred choice depends on the problem at hand and on the structural and parametric assumptions the researcher is willing to accept. The GMM estimator and the selection-correction give relatively similar results. The advantage of the GMM estimator is its applicability when there is more than one endogenous regressor and its robustness to the actual distribution of the count variable. The selection-correction estimator is only applicable with one endogenous regressor but provides explicit estimates of the correlation between error terms in a first-step estimation of the endogenous regressor and the second-step estimation of the count data model. If the researcher is willing to impose a specific distribution for the count variable a more efficient non-linear weighted least squares version of this estimator is applicable. The switching regression approaches are applicable only in the case of a categorical endogenous switching variable. The effect of the choice of a specific category (e.g. a specific health insurance contract) on the count variable (e.g. the number of visits) varies with individual characteristics. The matching estimator is the least parametric of the estimators. Only an estimate for the impact of a choice variable on an outcome is obtained as no functional form for the relation between exogenous regressors and an outcome is imposed. It is a “data-hungry” estimation approach as one should be able to observe all relevant determinants of the choice. Also, the choice has to be conditionally independent of the outcome.

The four estimators are applied to estimate induced changes to physician service utilization by choosing a higher deductible than is minimally required in Switzerland. The results indicate that the effect of choosing a higher deductible is overestimated when endogeneity is not controlled for. Most of the observed lower number of physician visits can be attributed to self-selection of individuals into insurance contracts with higher deductibles. In fact, no significant effect of such a choice on utilization is found in the GMM and selection-correction estimations. The SRE estimations provide an upper bound for the effect of the choice of a high deductible which is about the same as the effect found in multiplicative Poisson models which assume exogeneity of this choice. This upper bound is the result of remarkably different coefficients for some of the variables in the two subgroups of individuals who chose a high or low deductible. However it is unclear if the observed difference in coefficients reflects induced changes in utilization behavior, self-selection of individuals with different preferences into the respective insurance contracts or an ambiguity in the information contained in some of the variables. Only the matching estimator gives significant evidence that individuals with a high deductible might actually alter their utilization behavior. However, the validity of these results is doubtful as important determinants of the choice of the deductible are missing.

Generally, the results should be interpreted with caution. The health system reform was only introduced one year before the data was collected. It takes time for the insured to correctly understand the new system and to choose an optimal deductible. It can be hypothesized that those individuals who benefit from the choice of a higher deductible even without a change in their utilization behavior change their insurance contracts first. Individuals who expect to benefit from a higher deductible only when changing their behavior might do this later on. A replication of the results of this paper with data that was collected some years later and which contained information on previous health service utilization, health status and choice of deductible would probably give more conclusive results.

If one is willing to take the results at face value the question arises what the political implications should be. This depends mainly on a political point of view. If the main goal of offering a choice of deductible was to reduce moral hazard then this part of the reform seems to be a failure. If however, the goal was to offer contracts that offer premiums that were at least somewhat risk-related then the introduction of a choice of deductibles was successful.

The finding that the choice of a higher deductible has close to no impact on utilization behavior is hardly surprising. Insurance premiums can use a substantial part of income and the incentive to save money by taking the small risk of higher deductible gets bigger in regions with high premiums. But it is questionable if this risk is large enough to induce changes in physician utilization behavior as the difference in maximal out-of-pocket payments between insurance contracts with different deductibles is way below one percent of annual income for most households.

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Table 1: Descriptive Statistics

Variable	All (N=4057)	low deductible (N=3199)	high deductible (N=858)	matched low deductible
Age 15-24	0,047	0,054	0,024	0,017
Age 25-34	0,250	0,226	0,340	0,344
Age 35-44	0,225	0,211	0,280	0,255
Age 45-54	0,168	0,168	0,168	0,163
Age 55-64	0,139	0,150	0,096	0,105
Age 65-74	0,109	0,119	0,073	0,090
Age 75+	0,061	0,073	0,019	0,026
Foreigner	0,154	0,157	0,144	0,128
French/Italian Language	0,358	0,306	0,557	0,544
Metropolitan area	0,300	0,275	0,394	0,400
Large town	0,292	0,305	0,240	0,232
Small town	0,237	0,251	0,186	0,192
Secondary education	0,591	0,605	0,538	0,523
Tertiary education	0,292	0,265	0,396	0,404
Superior position	0,405	0,371	0,535	0,573
Self-employed	0,098	0,093	0,117	0,107
White collar	0,133	0,139	0,108	0,088
Full-time working	0,718	0,715	0,806	0,799
Part-time working	0,065	0,060	0,084	0,085
Retired	0,193	0,199	0,090	0,108
Unemployed	0,024	0,026	0,017	0,008
Chronic condition	0,133	0,148	0,073	0,106
Very good SAH	0,308	0,290	0,376	0,353
Good SAH	0,540	0,542	0,535	0,559
Underweight (BMI<20)	0,036	0,034	0,043	0,035
Overweight (BMI >30)	0,066	0,072	0,040	0,042
Accident last year	0,174	0,172	0,183	0,183
Alcohol g/day	17,00	16,72	18,15	19,19
Ex-smoker	0,250	0,262	0,204	0,212
Light smoker	0,017	0,017	0,016	0,017
Heavy smoker	0,368	0,369	0,367	0,379
Ex-user hard drugs	0,027	0,026	0,029	0,021
User soft drugs	0,035	0,035	0,038	0,031
Income	4084	3976	4507	4611
Suppl, Insurance	0,367	0,344	0,451	0,480
Urban canton	0,352	0,368	0,294	0,316
Geneva, Vaud	0,156	0,113	0,322	0,321
Roman canton	0,190	0,185	0,205	0,188
All physician visits	3,270	3,539	2,115	3,104
Primary physician visits	2,149	2,373	1,312	1,876
Specialist visits	1,121	1,198	0,803	1,227

Table 2: Estimates for Choice of Higher Deductible

	Probit		Probit	
Variable	Coefficient	t-value	Coefficient	t-value
Constant	-2,833	-5,525	-2,803	-5,472
Age 15-24	-0,642	-4,648	-0,642	-4,657
Age 35-44	-0,093	-1,423	-0,087	-1,339
Age 45-54	-0,328	-4,296	-0,310	-4,093
Age 55-64	-0,529	-5,985	-0,503	-5,767
Age 65-74	-0,437	-2,978	-0,411	-2,815
Age 75+	-0,851	-4,441	-0,828	-4,335
Foreigner	-0,158	-2,194	-0,153	-2,124
French/Italian	0,453	4,133	0,455	4,156
Metropolitan area	-0,074	-0,926	-0,075	-0,942
Large town	-0,110	-1,441	-0,114	-1,496
Small town	-0,037	-0,467	-0,039	-0,489
Secondary education	0,185	2,015	0,172	1,887
Tertiary education	0,302	2,969	0,288	2,848
Managerial profession	0,337	5,376	0,336	5,366
Self-employed	0,306	3,522	0,310	3,585
White collar	0,088	1,067	0,088	1,063
Part-time working	0,154	1,631	0,142	1,513
Retired	-0,056	-0,406	-0,060	-0,440
Unemployed	-0,046	-0,268	-0,042	-0,247
Chronic condition	-0,200	-2,414	-0,199	-2,413
Very good SAH	0,246	2,907	0,247	2,922
Good SAH	0,160	2,006	0,163	2,044
Underweight (BMI<20)	0,179	1,421	0,173	1,376
Overweight (BMI >30)	-0,181	-1,674	-0,181	-1,679
Alcohol g/day	0,003	1,516		
Alcohol g/day squared	0,000	-0,656		
Ex-smoker	-0,145	-2,186	-0,144	-2,187
Light smoker	-0,170	-0,920	-0,170	-0,924
Heavy smoker	-0,112	-1,968	-0,105	-1,902
Ex-user hard drugs	-0,215	-1,405		
User soft drugs	-0,024	-0,176		
Log Income	0,168	2,706	0,169	2,723
Suppl, Insurance	0,200	3,789	0,202	3,833
Urban canton	0,178	2,431	0,175	2,402
Geneva, Vaud	0,629	4,327	0,626	4,319
Roman canton	0,124	1,026	0,131	1,080
R^2	0,139		0,138	

Table 3a: All physician visits; GMM and SCE approaches

	Poisson multiplicative		GMM multiplicative		Terza 2-step NLS		Terza 2-step Poisson	
Variable	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
Constant	1,259	2,210	1,512	2,657	1,599	2,107	1,563	3,172
Age 15-24	0,373	2,783	0,512	3,524	0,288	1,733	0,531	4,343
Age 35-44	0,035	0,425	0,084	0,996	0,242	2,000	0,048	0,591
Age 45-54	0,170	2,091	0,287	3,145	0,134	1,150	0,349	4,530
Age 55-64	0,304	2,809	0,393	3,891	0,131	0,940	0,576	7,211
Age 65-74	0,140	1,066	0,265	2,066	-0,149	-0,941	0,478	4,217
Age 75+	0,375	2,598	0,529	3,761	0,157	0,890	0,806	5,987
Foreigner	0,057	0,719	0,149	1,810	0,209	2,303	-0,008	-0,099
French/Italian	0,236	4,141	0,062	0,793	-0,032	-0,351	-0,036	-0,619
Metropolitan area	-0,084	-0,979	-0,145	-1,647	-0,061	-0,574	-0,093	-1,389
Large town	-0,175	-2,183	-0,159	-1,977	-0,029	-0,300	-0,117	-1,721
Small town	-0,168	-2,021	-0,199	-2,453	0,028	0,233	-0,154	-2,062
Secondary education	0,026	0,331	0,035	0,452	-0,088	-0,916	-0,045	-0,555
Tertiary education	-0,025	-0,269	-0,059	-0,638	-0,150	-1,212	-0,140	-1,501
Managerial profession	-0,018	-0,290	-0,104	-1,549	-0,167	-1,767	-0,084	-1,366
Self-employed	-0,124	-1,274	-0,228	-2,153	-0,195	-1,504	-0,215	-2,506
White collar	-0,072	-0,907	-0,051	-0,633	-0,193	-2,045	-0,067	-0,917
Part-time working	0,342	2,571	0,289	2,173	0,108	0,633	0,303	3,761
Retired	0,314	2,772	0,254	2,243	0,530	3,912	0,206	2,001
Unemployed	0,110	0,790	0,132	0,896	0,083	0,572	0,021	0,125
Chronic condition	0,672	10,272	0,742	10,685	0,741	7,542	0,605	8,111
Very good SAH	-0,675	-8,211	-0,739	-8,661	-0,797	-7,123	-0,646	-8,119
Good SAH	-0,502	-7,545	-0,492	-7,306	-0,616	-6,393	-0,490	-6,710
Underweight	0,330	1,730	0,260	1,908	0,213	1,219	0,282	2,265
Overweight	0,167	1,799	0,216	2,156	-0,245	-2,343	0,297	4,362
Accident last year	0,467	7,772	0,477	7,687	0,573	6,312	0,393	6,076
Alcohol g/day	-0,003	-1,663	-0,003	-1,803	-0,006	-2,132	-0,003	-1,422
Alcohol g/day squared	0,000	1,252	0,000	1,566	0,000	2,382	0,000	0,262
Ex-smoker	0,148	2,060	0,154	2,258	0,149	1,891	0,161	2,699
Light smoker	0,280	1,315	0,176	0,837	1,115	3,567	0,311	0,838
Heavy smoker	-0,030	-0,488	-0,069	-1,112	0,071	0,840	0,085	1,523
Ex-user hard drugs	0,498	2,163	0,613	2,463	0,380	1,724	0,682	5,018
User soft drugs	-0,041	-0,297	-0,040	-0,277	-0,133	-0,612	-0,213	-1,458
Log of Income	-0,012	-0,180	-0,065	-0,939	-0,067	-0,755	-0,067	-1,138
Deductible	-0,344	-4,443	0,662	1,410	0,576	1,148	1,384	5,255
θ					-0,564	-2,323	-0,881	-7,018
σ^2							1,249	
ρ			Test stat.	p-value			-0,452	
Overidentification test			10,94	0,053				
Hausman endogeneity Test			4,721	0,030				

Table 4a: Primary physician visit; GMM and SCE approaches

	Poisson multiplicative		GMM multiplicative		Terza 2-step NLS		Terza 2-step Poisson	
Variable	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
Constant	1,235	2,292	1,630	2,847	3,119	2,306	1,479	3,150
Age 15-24	0,191	1,734	0,360	2,886	0,041	0,278	0,414	4,137
Age 35-44	0,017	0,231	0,068	0,876	0,066	0,585	0,061	0,839
Age 45-54	0,352	3,997	0,474	4,906	0,261	2,151	0,504	7,023
Age 55-64	0,482	5,462	0,611	6,347	0,361	2,371	0,658	8,451
Age 65-74	0,472	3,204	0,611	4,744	0,019	0,110	0,672	5,942
Age 75+	0,729	4,572	0,882	6,238	0,411	1,804	1,056	7,861
Foreigner	0,004	0,053	0,060	0,800	0,281	2,930	-0,090	-1,138
French/Italian	0,081	1,463	-0,101	-1,288	-0,221	-1,734	-0,125	-2,197
Metropolitan area	-0,238	-3,040	-0,270	-3,262	-0,410	-2,171	-0,244	-3,493
Large town	-0,184	-2,523	-0,140	-1,878	-0,230	-1,262	-0,152	-2,164
Small town	-0,104	-1,305	-0,102	-1,282	-0,315	-1,570	-0,101	-1,437
Secondary education	-0,105	-1,366	-0,099	-1,294	0,000	-0,003	-0,084	-1,181
Tertiary education	-0,159	-1,712	-0,189	-2,019	-0,026	-0,185	-0,227	-2,646
Managerial profession	-0,080	-1,187	-0,179	-2,571	-0,077	-0,864	-0,101	-1,811
Self-employed	-0,020	-0,208	-0,137	-1,400	0,046	0,330	-0,101	-1,238
White collar	-0,068	-0,851	-0,098	-1,336	0,107	0,529	-0,069	-0,918
Part-time working	0,071	0,519	-0,064	-0,576	-0,020	-0,165	-0,024	-0,281
Retired	0,266	2,122	0,185	1,661	0,643	4,351	0,111	1,066
Unemployed	0,230	1,586	0,265	1,691	0,167	1,000	0,249	1,816
Chronic condition	0,684	9,798	0,771	10,661	0,649	6,460	0,618	9,463
Very good SAH	-0,664	-8,831	-0,753	-9,181	-0,773	-5,775	-0,690	-9,369
Good SAH	-0,423	-6,591	-0,458	-6,645	-0,529	-3,659	-0,407	-6,141
Underweight	0,176	1,304	0,234	1,702	0,295	1,422	0,184	1,396
Overweight	0,209	2,267	0,263	2,579	-0,258	-1,924	0,373	7,205
Accident last year	0,418	7,169	0,416	6,906	0,286	3,136	0,319	5,147
Alcohol g/day	-0,004	-1,947	-0,004	-2,326	-0,008	-2,412	-0,003	-2,003
Alcohol g/day squared	0,000	1,631	0,000	2,092	0,000	1,656	0,000	1,042
Ex-smoker	0,171	2,712	0,222	3,384	0,402	2,357	0,100	1,724
Light smoker	-0,036	-0,255	0,013	0,082	-0,200	-0,824	0,004	0,025
Heavy smoker	0,031	0,521	0,034	0,576	0,295	2,748	0,039	0,765
Ex-user hard drugs	0,167	0,985	0,331	1,690	0,334	1,950	0,079	0,429
User soft drugs	-0,078	-0,502	-0,064	-0,391	-0,086	-0,455	-0,093	-0,538
Log of Income	-0,046	-0,711	-0,113	-1,623	-0,321	-1,961	-0,083	-1,487
Deductible	-0,276	-3,599	0,927	1,689	0,858	1,248	1,065	4,013
θ					-0,596	-1,798	-0,710	-5,430
σ^2							1,071	
ρ			Test stat.	p-value			-0,553	
Overidentification test			6,401	0,269				
Hausman endogeneity Test			4,901	0,027				

Table 3b: All physician visits; SRE approaches

	Poisson				Without Zero				Without Zero Exogenous			
	high deductible		low deductible		high deductible		low deductible		high deductible		low deductible	
Variable	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
Constant	-0,016	-0,031	1,239	9,250	1,163	1,387	2,003	8,614	0,628	1,143	2,796	13,218
Age 15-24	0,291	3,164	0,223	6,489	0,249	1,527	0,175	3,244	0,113	0,726	0,191	3,982
Age 35-44	0,013	0,301	-0,003	-0,165	0,125	1,569	0,001	0,029	0,122	1,682	0,054	1,647
Age 45-54	0,029	0,509	0,134	6,068	0,132	1,263	0,141	3,696	0,037	0,424	0,117	3,394
Age 55-64	0,249	4,038	0,173	6,912	0,383	3,564	0,140	3,529	0,548	5,940	0,077	2,158
Age 65-74	0,314	3,707	0,111	3,310	0,440	2,806	-0,018	-0,33	0,487	3,676	-0,262	-5,270
Age 75+	0,640	6,519	0,330	8,466	0,588	3,231	0,181	3,044	0,711	4,403	-0,065	-1,221
Foreigner	-0,269	-4,469	0,100	5,300	-0,307	-3,300	0,056	1,763	-0,530	-5,804	0,118	4,198
French/Italian	0,349	3,917	0,096	4,849	0,366	4,588	0,049	2,036	0,433	7,577	0,060	2,800
Metropolitan area	-0,097	-2,249	-0,062	-3,248	-0,165	-2,015	-0,058	-1,715	-0,107	-1,416	-0,051	-1,708
Large town	-0,187	-3,609	-0,081	-4,444	-0,274	-3,108	-0,066	-2,032	-0,283	-3,430	-0,098	-3,367
Small town	-0,139	-2,596	-0,093	-4,874	-0,222	-2,325	-0,090	-2,626	-0,077	-0,883	-0,155	-4,998
Secondary	-0,165	-2,745	0,041	2,105	-0,217	-2,061	0,010	0,306	-0,310	-3,286	0,034	1,129
Tertiary education	-0,214	-3,040	0,013	0,543	-0,305	-2,599	0,008	0,188	-0,471	-4,638	0,027	0,729
Managerial	0,163	3,012	-0,017	-0,964	0,070	0,919	-0,036	-1,275	0,247	3,434	-0,101	-3,940
Self-employed	0,096	1,457	-0,113	-4,332	-0,019	-0,170	-0,147	-3,368	0,024	0,237	-0,240	-5,950
White collar	-0,263	-3,566	-0,001	-0,065	-0,371	-2,143	-0,029	-0,861	-0,297	-2,532	-0,087	-2,896
Part-time working	0,087	1,422	0,171	7,109	-0,011	-0,042	0,145	3,26	-0,105	-1,123	0,322	8,629
Retired	0,403	4,977	0,223	8,477	0,153	1,063	0,241	5,312	-0,065	-0,563	0,401	10,350
Unemployed	-0,105	-0,534	0,229	6,525	-0,425	-1,479	0,234	3,64	-0,454	-1,601	0,141	2,419
Chronic condition	0,560	10,810	0,525	32,094	0,439	5,108	0,456	17,785	0,466	6,104	0,533	23,424
Very good SAH	-0,213	-3,879	-0,612	-28,155	-0,161	-1,653	-0,508	-14,879	-0,168	-1,972	-0,580	-18,955
Good SAH	-0,175	-3,360	-0,353	-22,171	-0,185	-2,090	-0,294	-11,204	-0,279	-3,465	-0,403	-17,326
Underweight	-0,332	-3,737	0,230	7,547	-0,223	-1,137	0,194	3,647	0,501	4,533	0,222	4,851
Overweight	0,276	3,519	0,097	4,443	0,034	0,290	0,034	0,875	-0,138	-1,224	-0,051	-1,430
Accident last year	0,462	10,393	0,374	23,471	0,314	4,421	0,203	7,561	0,278	4,568	0,246	10,274
Ex-smoker	0,065	1,437	0,090	5,540	-0,005	-0,058	0,074	2,68	0,139	1,884	0,099	3,954
Light smoker	0,527	5,054	-0,038	-0,663	0,410	2,185	-0,001	-0,014	0,281	1,575	0,547	8,405
Heavy smoker	0,194	5,381	-0,059	-3,978	0,201	2,934	0,003	0,117	0,332	5,418	-0,022	-0,890
Log of Income	0,062	1,355	-0,022	-1,323	-0,014	-0,136	-0,075	-2,617	0,058	0,869	-0,144	-5,523
ρ	-0,176	-1,039	0,071	0,622	-0,006	-0,101	0,001	0,015				
φ					0,358	11,072	0,227	25,045	0,372	6,523	0,236	27,014

Table 4b: Primary physician visits; SRE approaches

	Poisson, Censored				Without Zero, Censored				Without Zero, Exogenous			
	high deductible		low deductible		high deductible		low deductible		high deductible		low deductible	
Variable	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
Constant	-0,281	-0,397	1,570	9,239	0,462	0,769	2,357	14,310	1,409	1,993	2,716	10,410
Age 15-24	-0,130	-0,590	0,150	3,063	-0,383	-1,158	0,039	0,791	-0,423	-1,524	0,033	0,460
Age 35-44	0,011	0,186	0,042	1,495	-0,009	-0,119	0,011	0,378	-0,075	-0,753	0,050	1,070
Age 45-54	0,040	0,543	0,316	10,886	0,127	1,308	0,282	10,146	0,097	0,831	0,291	6,350
Age 55-64	0,379	4,952	0,411	12,812	0,429	4,694	0,376	12,524	0,338	2,651	0,383	8,190
Age 65-74	0,280	2,488	0,380	9,117	0,287	2,185	0,235	5,960	0,281	1,685	0,086	1,400
Age 75+	0,760	6,466	0,560	11,624	0,580	4,457	0,376	8,827	0,760	3,875	0,280	4,360
Foreigner	-0,270	-3,182	0,090	3,871	-0,382	-4,100	0,071	3,021	-0,574	-4,791	0,122	3,390
French/Italian	0,211	1,924	-0,042	-1,669	0,278	4,239	-0,025	-1,191	0,246	3,324	-0,038	-1,390
Metropolitan area	-0,149	-2,441	-0,187	-7,715	-0,218	-2,699	-0,164	-6,761	-0,160	-1,547	-0,215	-5,670
Large town	-0,140	-1,929	-0,089	-3,908	-0,345	-3,961	-0,085	-3,720	-0,261	-2,442	-0,152	-4,330
Small town	-0,002	-0,030	-0,076	-3,261	-0,124	-1,549	-0,082	-3,575	-0,077	-0,682	-0,170	-4,620
Secondary	-0,227	-2,829	0,003	0,145	-0,285	-2,680	-0,025	-1,044	-0,476	-4,111	-0,006	-0,160
Tertiary education	-0,413	-4,508	-0,032	-1,101	-0,439	-3,673	-0,008	-0,269	-0,586	-4,527	0,019	0,420
Managerial	0,220	2,920	-0,086	-3,865	0,150	1,989	-0,099	-4,610	0,127	1,300	-0,085	-2,610
Self-employed	0,219	2,346	-0,073	-2,336	0,216	2,141	-0,122	-4,099	0,225	1,739	-0,101	-2,140
White collar	-0,120	-1,334	-0,033	-1,391	-0,210	-1,893	-0,057	-2,363	-0,142	-0,986	-0,025	-0,680
Part-time working	0,069	0,843	0,023	0,698	0,224	2,183	0,009	0,280	0,360	3,012	-0,057	-0,990
Retired	0,480	4,566	0,220	7,098	0,361	3,457	0,227	7,684	0,357	2,427	0,371	8,040
Unemployed	0,190	0,848	0,278	6,470	0,089	0,286	0,288	6,201	0,079	0,247	0,212	2,880
Chronic condition	0,521	8,024	0,504	26,142	0,401	5,421	0,480	27,175	0,399	3,960	0,558	19,940
Very good SAH	-0,241	-3,173	-0,638	-23,388	-0,155	-1,623	-0,565	-21,937	-0,052	-0,449	-0,624	-15,720
Good SAH	-0,159	-2,184	-0,347	-18,150	-0,135	-1,387	-0,315	-17,693	-0,034	-0,309	-0,366	-12,770
Underweight	-0,530	-3,345	0,269	7,112	-0,383	-2,195	0,271	7,700	0,460	2,603	0,335	5,860
Overweight	0,239	2,086	0,112	4,252	-0,091	-0,586	0,046	1,854	-0,160	-1,142	0,001	0,030
Accident last year	0,462	7,938	0,315	15,329	0,385	6,271	0,144	7,072	0,388	4,638	0,160	5,060
Ex-smoker	0,139	2,324	0,104	5,157	0,005	0,069	0,076	3,961	0,035	0,373	0,141	4,560
Light smoker	0,390	1,734	-0,160	-1,784	0,165	0,367	-0,207	-1,727	-0,109	-0,414	-0,205	-1,580
Heavy smoker	0,212	4,523	-0,021	-1,071	0,252	4,371	0,040	2,070	0,334	4,020	0,097	3,140
Log of Income	0,059	0,950	-0,104	-4,864	0,035	0,486	-0,148	-7,359	-0,066	-0,767	-0,188	-5,850
ρ	-0,191	-0,950	0,078	0,665	0,030	0,234	0,049	0,453				
φ					0,430	6,949	0,269	19,518	0,427	3,299	0,277	20,296

Figure 1a: All physician visits

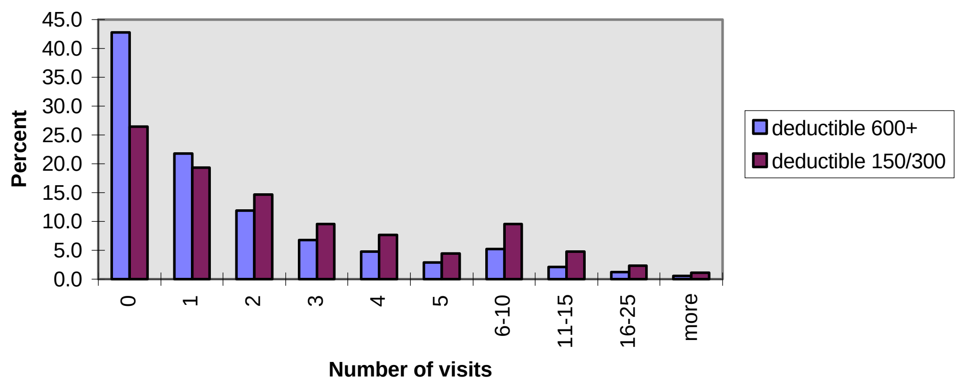


Figure 1b: Primary physician visits

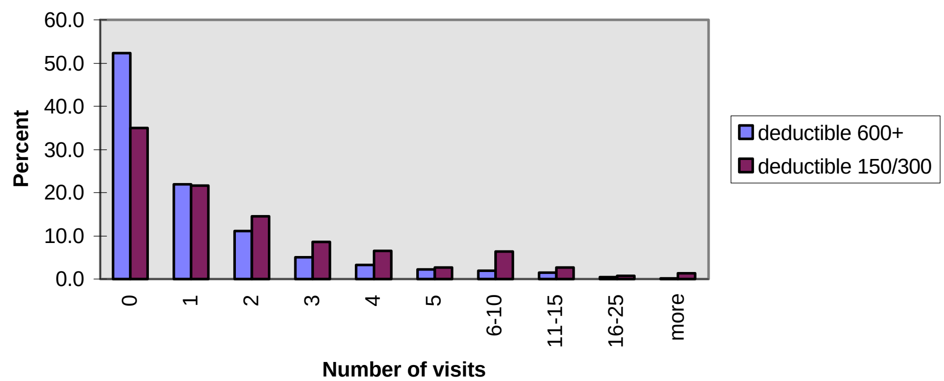
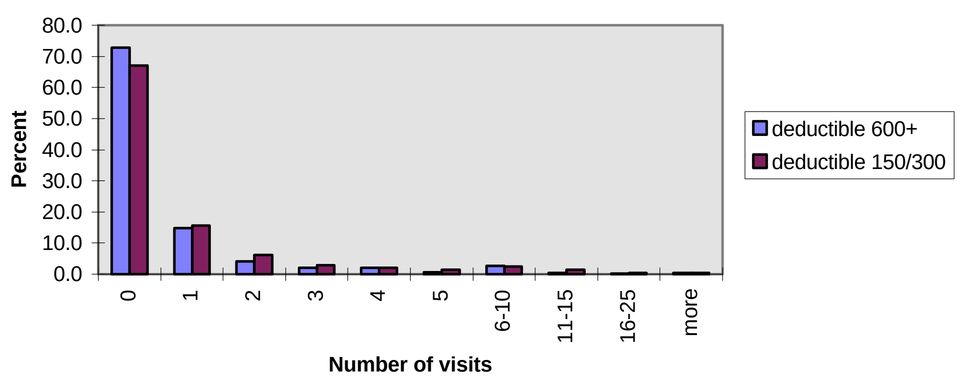


Figure 1c: Specialist visits



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